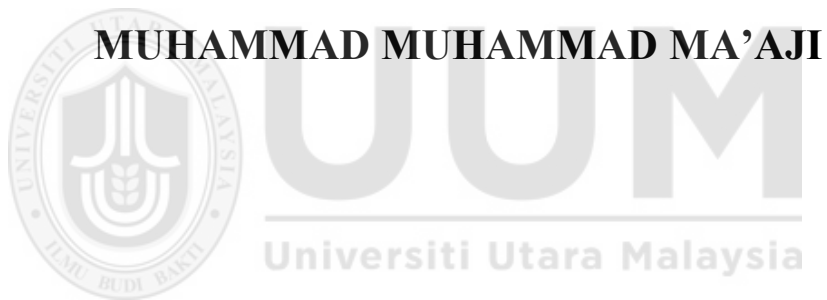


The copyright © of this thesis belongs to its rightful author and/or other copyright owner. Copies can be accessed and downloaded for non-commercial or learning purposes without any charge and permission. The thesis cannot be reproduced or quoted as a whole without the permission from its rightful owner. No alteration or changes in format is allowed without permission from its rightful owner.



**DETERMINANTS OF SME's FAILURE IN MALAYSIA
AND NIGERIA**



**DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
November 2018**

DETERMINANTS OF SME's FAILURE IN MALAYSIA AND NIGERIA

By

MUHAMMAD MUHAMMAD MA'AJI



UUM
Universiti Utara Malaysia

**Thesis Submitted to
Othman Yeop Abdullah Graduate School of Business,
Universiti Utara Malaysia,
in Fulfillment of the Requirement for the Degree of Doctor of Philosophy**



Kolej Perniagaan
(College of Business)
Universiti Utara Malaysia

PERAKUAN KERJA TESIS / DISERTASI
(Certification of thesis / dissertation)

Kami, yang bertandatangan, memperakukan bahawa
(We, the undersigned, certify that)

MUHAMMAD MUHAMMAD MA'AJI (900709)

calon untuk Ijazah

DOCTOR OF PHILOSOPHY (FINANCE & BANKING)

(candidate for the degree of)

telah mengemukakan tesis / disertasi yang bertajuk:

(has presented his/her thesis / dissertation of the following title):

DETERMINANTS OF SME'S FAILURE IN MALAYSIA AND NIGERIA

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.

(as it appears on the title page and front cover of the thesis / dissertation).

Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan, sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada:

25 Jun 2018.

(That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on:

25 June 2018).

Pengerusi Viva
(Chairman for Viva)

: **Assoc. Prof. Dr. Kamarun Nisham Taufil Mohd**

Tandatangan
(Signature)

Pemeriksa Luar
(External Examiner)

: **Prof. Dr. Shamsul Nahar Abdullah**

Tandatangan
(Signature)

Pemeriksa Dalam
(Internal Examiner)

: **Assoc. Prof. Dr. Rohani Md Rus**

Tandatangan
(Signature)

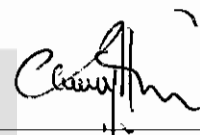
Tarikh: **25 Jun 2018**
(Date)

Nama Pelajar : **Muhammad Muhammad Ma'aji**
(Name of Student)

Tajuk Tesis / Disertasi : **Determinants of SME's Failure in Malaysia and Nigeria**
(Title of the Thesis / Dissertation)

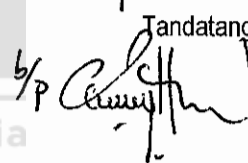
Program Pengajian : **Doctor of Philosophy (Finance & Banking)**
(Programme of Study)

Nama Penyelia/Penyelia-penyelia : **Prof. Dr. Nur Adiana Hiau Abdullah**
(Name of Supervisor/Supervisors)



Tandatangan

Nama Penyelia/Penyelia-penyelia : **Dr. Khaw Lee Hwei**
(Name of Supervisor/Supervisors)



Tandatangan

PERMISSION TO USE

In presenting this thesis in fulfilment of the requirements for a Post Graduate degree from the Universiti Utara Malaysia (UUM), I agree that the Library of this university may make it freely available for inspection. I further agree that permission for copying this thesis in any manner, in whole or in part, for scholarly purposes may be granted by my supervisor(s) or in their absence, by the Dean of Othman Yeop Abdullah Graduate School of Business where I did my thesis. It is understood that any copying or publication or use of this thesis or parts of it for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the UUM in any scholarly use which may be made of any material in my thesis.

Request for permission to copy or to make other use of materials in this thesis in whole or in part should be addressed to:

Dean of Othman Yeop Abdullah Graduate School of Business

Universiti Utara Malaysia

06010 UUM Sintok

Kedah Darul Aman



UUM
Universiti Utara Malaysia

ABSTRACT

Small and medium-sized enterprises (SMEs) play an important role toward economic development worldwide. Predicting bankruptcy among SMEs can have a significant impact on the economy as an effective early warning signal. This study develops bankruptcy prediction models for Malaysian and Nigerian SMEs by combining financial, non-financial, corporate governance and macroeconomic variables using the logistic regression and artificial neural network (ANN) methods. The accuracy rates obtained by those two methods were then compared. In developing the estimated model, 1,556 (632) SMEs from the manufacturing sector in Malaysia (Nigeria) are selected. Three sub-samples are created representing 3-years, 2-years and 1-year prior to bankruptcy, with total observations of 666 (344), 470 (172) and 420 (116) respectively. Each sub-sample comprises 50 percent non-bankrupt and 50 percent bankruptcy firms, from years 2000 to 2014. The findings show that four of the financial variables, namely, lower profitability, high leverage, insufficient liquidity and high operating expenses are associated with bankruptcy among SMEs in Malaysia and Nigeria. As for the non-financial variables, the results indicate that young SMEs and those located in less industrialised states are more likely to go bankrupt. In addition, the corporate governance variables, such as number of directors, independent director, managing director duality, controlling shareholder, ethnicity and gender of managing director are found significant. Moreover, high unemployment rate is associated with bankruptcy among SMEs in Malaysia and Nigeria, while high inflation rate as well as lending rate are associated with SMEs bankruptcy only in Nigeria. The result shows that the ANN model leads to a higher predictive accuracy rate compared to the logistic regression model for Malaysia and Nigeria. The study reveals that SMEs should increase the number of independent directors, discourage CEO duality and reduce ownership concentration. Financial institutions could use this study as a reference model to manage credit risk of SMEs while the government agencies may use it to improve their existing policies.

Keywords: bankruptcy prediction, corporate governance, logistic regression, neural network, small and medium-sized enterprises.

ABSTRAK

Industri kecil dan sederhana (IKS) memainkan peranan penting ke arah pembangunan ekonomi di seluruh dunia. Ramalan kebangkrutan dalam kalangan IKS boleh memberikan kesan yang ketara kepada ekonomi kerana ia berfungsi sebagai satu isyarat awal yang berkesan. Kajian ini membangunkan model ramalan kebangkrutan bagi IKS di Malaysia dan juga Nigeria dengan menggabungkan pemboleh ubah kewangan, bukan kewangan, tadbir urus korporat dan ekonomi makro dengan menggunakan regresi logistik dan kaedah rangkaian neural tiruan atau artificial neural network (ANN). Kadar ketepatan yang diperolehi melalui dua kaedah tersebut kemudiannya dibandingkan. Pembangunan model anggaran ini dilakukan melalui pemilihan 1,556 (632) IKS daripada sektor pembuatan di Malaysia (Nigeria). Tiga sub-sampel diwujudkan bagi mewakili 3-tahun, 2-tahun dan 1-tahun sebelum bankrap, dengan 666 (344), 470 (172) dan 420 (116) pemerhatian masing-masing. Setiap sub-sampel terdiri daripada 50 peratus syarikat bukan-bankrap dan 50 peratus syarikat bankrap, daripada tahun 2000 hingga 2014. Dapatan kajian menunjukkan bahawa antara empat daripada pemboleh ubah kewangan, iaitu keuntungan yang rendah, leveraj yang tinggi, kekurangan kecairan dan perbelanjaan operasi yang tinggi dikaitkan dengan kebangkrutan IKS di Malaysia dan Nigeria. Bagi pemboleh ubah bukan kewangan pula, IKS baru dan syarikat yang terletak di negeri yang perindustriannya kurang maju, adalah lebih cenderung untuk menjadi bankrap. Di samping itu, antara pemboleh ubah tadbir urus korporat yang didapati signifikan adalah bilangan pengarah, pengarah bebas, dualiti pengarah urusan, pemegang saham yang berkuasa, etnik dan jantina pengarah urusan. Selain itu, kadar pengangguran yang tinggi mempunyai kaitan dengan kebangkrutan dalam kalangan IKS di Malaysia dan Nigeria, manakala kadar inflasi yang tinggi serta kadar pinjaman dikaitkan dengan kebangkrutan IKS hanya di Nigeria. Hasil kajian menunjukkan bahawa model ANN memberikan kadar kejituan ramalan yang lebih tinggi berbanding model regresi logistik bagi Malaysia dan Nigeria. Kajian ini mendedahkan bahawa IKS perlu meningkatkan bilangan pengarah bebas, mengelakkan dualiti atau penggandaan tugas CEO dan mengurangkan konsentrasi pemilik saham. Institusi kewangan boleh menggunakan kajian ini sebagai model rujukan untuk menangani risiko kredit IKS, manakala agensi kerajaan boleh menggunakannya untuk menambahbaik dasar yang sedia ada.

Kata Kunci: meramal kebangkrutan, tadbir urus korporat, regresi logistik, kaedah rangkaian neural tiruan, Industri kecil dan sederhana.

ACKNOWLEDGEMENT

In the Name of Allah, Most Gracious, Most Merciful. All praise be to Allah, Lord of the universe. First and foremost, I must acknowledge my limitless appreciation to Allah, the Ever-Magnificent; the Ever-Thankful, for His help, Knowledge, Guidance and Blessings. I am very sure that this work would have never become truth, without His Guidance.

I am so much grateful to the Postgraduate Scholarship Scheme and Student Affairs Department (HEP) at the Universiti Utara Malaysia for the award of scholarship and to making it possible for me to study here. I give deep thanks to all the staffs at the HEP for their support. I would like to sincerely thank my lovable supervisors, Prof. Dr. Nur Adiana Hiau Abdullah and Dr. Khaw Lee Hwei whom have not only been patient, affable and helpful in guiding me towards completing this thesis, but also for helping me develop some vital virtue within me. I appreciate their invaluable knowledge, feedback and recommendations that make this a better research. I consider it a great privilege to do my doctoral programme under your guidance.

I acknowledge constructive feedbacks from my examiners, Prof. Dr. Shamsul Nahar Abdullah, Asoc. Prof. Rohani Md Rus and Asoc. Prof. Kamarun Nisham Taufil Mohd for the gainful comments and suggestions given at the doctoral research defense. My profound gratitude goes to all the staff of Companies Commission Malaysia (SSM) and Corporate Affairs Commission Nigeria (CAC) that assisted during the process of data collection. I thank the editorial board of Asian Academy of Management Journal of Accounting & Finance (AAMJAF) and International Journal of Business and Society (IJBS) and the anonymous reviewers for their gainful comments and constructive criticism.

I cannot begin to express my gratitude to my family for all of the love, support, encouragement and prayers they have sent my way along this journey. My exceptional and grateful thanks are accorded to my beloved and wonderful late parents, Alh. Kawu Muhammad Ma'aji and Laraba Mika'il, who painstakingly laid the foundation for my education giving it all it takes. They have steadfastly prayed and faithfully sought God's guidance, grace and blessing for me to succeed in my career. Your unconditional love and support has meant the world to me, I hope that I have made you proud and pray may your souls continue to rest in perfect peace, Amin. The past years have not been an easy ride but I will always be thankful to my beloved siblings who gave me the hope of a family to count on when times are rough. I will always be grateful for your prayers and support in all aspects and I am so proud of all of your accomplishments and share in all of the joys in your lives. May God continue to strengthen our bond. To my grandparents, especially Hajiya Hasiya Adamu and Malam Mika'il Sarina, my uncles and aunties, thank you all for your prayers, support and believing in me.

I am highly indebted to all my dear friends at UUM and back home. May Allah reward you all for the unflinching support at the different stages of the journey. I appreciate all your prayers and support. You are more than just friends. My acknowledgement will not be complete without appreciating the opportunities and

support given to me by CamEd Business School president, Casey Barnett and would like to thanks all my colleagues there for their prayers, encouragement and support.

I wish to acknowledge the contributions of all those who assisted me in one way or another. Your untiring guidance, hard work and encouragement were invaluable, without which the research would not have been possible.

For all this, I truly thank you all and may God bless you richly and abundantly, Amin.

I dedicate this research to my late parents
~~ Alh. Kawu Muhammad Ma'aji and Laraba Mika'il ~~



TABLE OF CONTENT

TITLE PAGE	i
CERTIFICATION OF THESIS WORK	iv
PERMISSION TO USE	v
ABSTRACT (ENGLISH)	vi
ABSTRAK (BAHASA MELAYU)	vii
ACKNOWLEDGEMENT	viii
TABLE OF CONTENTS	x
LIST OF TABLES	xiii
LIST OF FIGURES	xv
LIST OF APPENDICES	xvi
LIST OF ABBREVIATIONS	xvii
CHAPTER ONE: INTRODUCTION	1
1.1 Background of Study	1
1.2 SMEs in Malaysia	6
1.3 SMEs in Nigeria	10
1.4 Problem Statement	14
1.5 Research Questions	18
1.6 Research Objectives	19
1.7 Significant of Study	19
1.8 Scope of the study	22
1.9 Organisation of the Study	23
CHAPTER TWO: LITERATURE REVIEW	25
2.1 Introduction	25
2.2 The Underlying Theories	25
2.2.1 Modigliani and Miller (MM)	26
2.2.2 Trade-off Theory	27
2.2.3 Pecking Order Theory	29
2.2.4 Agency Theory	31
2.2.5 Stewardship Theory	34
2.3 Empirical Evidence of Business Failure	35
2.3.1 Evolution of Business Failure Prediction Studies	36
2.3.2 Empirical Evidence from Developed Countries	39
2.3.3 Empirical Evidence from the Developing Countries	52
2.4 Determinant of SMEs Failure Prediction Studies	58
2.4.1 Financial Indicators	59
2.4.2 Non-Financial Indicators	62
2.4.3 Corporate Governance Indicators	64
2.4.4 Macroeconomic Indicators	68
2.5 Failure Prediction Methods and Accuracy Rates	72
2.5.1 Multiple Discriminant Analysis	76
2.5.2 Logit Model	78
2.5.3 Artificial Neural Network	81
2.6 Chapter Summary	85
CHAPTER THREE: METHODOLOGY	87
3.1 Introduction	87

3.2	Data Collection and Sample Selection	87
3.3	Research Framework	93
3.4	Hypotheses Development	99
3.4.1	Financial Indicators	99
3.4.1.1	Profitability Ratios	99
3.4.1.2	Leverage Ratios	100
3.4.1.3	Liquidity Ratios	102
3.4.1.4	Activity Ratios	103
3.4.1.5	Size	105
3.4.2	Non-Financial Indicators	106
3.4.2.1	Business Location	106
3.4.2.2	Firm Age	110
3.4.3	Governance Indicators	111
3.4.3.1	CEO Duality	112
3.4.3.2	Board Size	113
3.4.3.3	Controlling Shareholder	114
3.4.3.4	Independent Director	115
3.4.3.5	Gender of Managing Director	116
3.4.3.6	Ethnicity of Managing Director	119
3.4.4	Macroeconomic Indicators	120
3.4.4.1	Gross Domestic Product	121
3.4.4.2	Unemployment Rate	122
3.4.4.3	Inflation Rate	123
3.4.4.4	Interest Rate	124
3.5	Methods	126
3.5.1	Logistic Regression s	126
3.5.2	Artificial Neural Network	131
3.5.3	Endogeneity	136
3.6	Chapter Summary	141

CHAPTER FOUR: EMPIRICAL RESULTS AND DISCUSSION		142
4.1	Introduction	142
4.2	Malaysian SMEs	142
4.2.1	Descriptive Statistics of Malaysian Sample	143
4.2.2	Diagnostic Tests for Logistic Regression	150
4.2.2.1	Multicollinearity	150
4.2.2.2	Model Specification Test	154
4.2.2.3	Test for Model Fit	156
4.2.3	Logistic Regression Analysis	157
4.2.3.1	Model 1: Financial and Non-financial Variables	157
4.2.3.2	Model 2: Governance and Macroeconomic Variables	163
4.2.3.3	Model 3: Model 1 and Model 2 Combined	167
4.2.4	Models Performance and Validation under Logistic Regression	172
4.2.4.1	Robustness Check on the Classification Accuracy of the Logistic Regression Models	174
4.2.5	Endogeneity Test	179
4.2.6	Artificial Neural Network Analysis of Malaysian Sample	186
4.2.7	Models Performance and Validation under ANN	189
4.2.8	Comparison of the Accuracy Rate between Logistic Regression and ANN	190

4.2.9	Summary of the hypothesis of Malaysian Sample	192
4.3	Nigerian SMEs	194
4.3.1	Descriptive Statistics of Nigeria Sample	194
4.3.2	Diagnostic Tests for Logistic Regression	201
4.3.2.1	Multicollinearity	201
4.3.2.2	Model Specification Test	206
4.3.2.3	Test for Model Fit	207
4.3.3	Logistic Regression Analysis	207
4.3.3.1	Model 1: Financial and Non-financial Variables	208
4.3.3.2	Model 2: Governance and Macroeconomic Variables	212
4.3.3.3	Model 3: Model 1 and Model 2 Combined	216
4.3.4	Models Performance and Validation under Logistic Regression	221
4.3.4.1	Robustness Check on the Classification Accuracy of the Logistic Regression Models	223
4.3.5	Endogeneity Test	228
4.3.6	Artificial Neural Network Analysis of Nigerian Sample	234
4.3.7	Models Performance and Validation under ANN	238
4.3.8	Comparison of the Accuracy Rate between Logistic Regression and ANN	239
4.3.9	Summary of the hypothesis of Nigerian Sample	241
4.4	Comparison of Significant Predictors of SMEs Bankruptcy between Malaysia and Nigeria	243
4.5	Chapter Summary	249
CHAPTER FIVE: CONCLUSION		251
5.1	Introduction	251
5.2	Summary of the Findings	251
5.3	Implications of the Study	257
5.4	Limitations of the Study	261
5.5	Recommendation for Future Research	262
REFERENCES		264
APPENDICES		300

LIST OF TABLES

TABLES		PAGE
Table 1.1	Definition of SMEs Manufacturing Sector in Malaysia	6
Table 1.2	Definition of SMEs in Nigeria	11
Table 2.1	Summary of Studies on SMEs	73
Table 3.1	Summary of the Sample Selection	92
Table 3.2	Definition of variables	96
Table 3.3	Definition of Instrumental Variables	135
Table 4.1	Descriptive Statistics of Malaysia Sample	144
Table 4.2	Descriptive Statistics of Malaysia Sample	145
Table 4.3	Descriptive Statistics of Malaysia Sample	146
Table 4.4	Pearson Correlation Analysis of Malaysian Sample	151
Table 4.5	Variance inflating factor	153
Table 4.6	Model Specification Test (Linktest) Malaysian Sample	155
Table 4.7	Models Fit Test Malaysian Sample	157
Table 4.8	Logistic regression of Malaysian Sample	160
Table 4.9	Logistic Regression Classification Rate for both Estimated and Holdout Sample for Malaysia	173
Table 4.10	ROC classification rate and Brier Score for Malaysia Models	175
Table 4.11	Brier Score for Malaysian Models	179
Table 4.12	The results of endogeneity test for Model 2	182
Table 4.13	The results of endogeneity test for Model 3	183
Table 4.14	Durbin-Wu-Hausman test and Hansen-Sargen test for model 3 Malaysian sample	184
Table 4.15	Artificial Neural Network of Malaysian Sample	187
Table 4.16	ANN Classification rate for both estimated and holdout sample for Malaysia	189
Table 4.17	Misclassification rates of the different models for Malaysia	191
Table 4.18	The summary of the hypothesis and the finding for Malaysia	193
Table 4.19	Descriptive Statistics of Nigerian Sample	196
Table 4.20	Descriptive Statistics of Nigerian Sample	197
Table 4.21	Descriptive Statistics of Nigerian Sample	198
Table 4.22	Pearson Correlation Analysis of Nigerian Sample	203
Table 4.23	Variance inflating factor	205
Table 4.24	Model Specification Test (Linktest) of Nigerian Sample	206
Table 4.25	Models Fit Test Nigerian Sample	207
Table 4.26	Logistic regression of Nigerian Sample	209
Table 4.27	Logistic Regression Classification Rate for both Estimated and Holdout Sample for Nigeria	222
Table 4.28	ROC classification rate and Brier Score for Nigeria Models	224
Table 4.29	Brier Score for Nigeria Models	227
Table 4.30	The results of endogeneity test for Model 2	230
Table 4.31	The results of endogeneity test for Model 3	231
Table 4.32	Durbin-Wu-Hausman test and Hansen-Sargen test for model 2 and 3 Nigerian sample	233
Table 4.33	Artificial Neural Network of Nigerian Sample	235
Table 4.34	ANN Classification rate for both estimated and holdout sample	238

for Nigeria

Table 4.35	Misclassification rates of the different models for Nigeria	239
Table 4.36	The summary of the hypothesis and the finding for Nigeria	241



LIST OF FIGURES

FIGURES	PAGE
Figure 1.1 Contribution of SMEs to Employment	2
Figure 1.2 SMEs' Contribution to GDP Growth from 2005 to 2014	7
Figure 1.3 Comparison of SMEs and Large Firms' Contributions to GDP	8
Figure 1.4 Proportion of SMEs by the Manufacturing Sub-sectors	10
Figure 1.5 Commercial Banks Loan to SMEs	22
Figure 1.6 Percentage Share of SMEs Categories in Malaysia	23
Figure 2.1 Modigliani and Miller (MM) Proposition I	26
Figure 2.2 Trade-off theory	28
Figure 2.3 The Agency Relationships in a Company	31
Figure 3.1 Conceptual Research Framework	95
Figure 3.2 Multilayer Perceptron (MLP)	132
Figure 4.1 Comparison of ROC curves between models developed using 3-year prior sample	175
Figure 4.2 Comparison of ROC curves between models developed using 2-year prior sample	177
Figure 4.3 Comparison of ROC curves between models developed using 1-year prior sample	177
Figure 4.4 Comparison of ROC curves between models developed using 3-year prior sample	224
Figure 4.5 Comparison of ROC curves between models developed using 2-year prior sample	225
Figure 4.6 Comparison of ROC curves between models developed using 1-year prior sample	226

LIST OF APPENDICES

APPENDIX		PAGE
Appendix 1	Logistic regression Malaysian samples	300
Appendix 2a	3-year prior to bankruptcy sample endogeneity test	319
Appendix 2b	2-year prior to bankruptcy sample endogeneity test	324
Appendix 2c	1-year prior to bankruptcy sample endogeneity test	327
Appendix 3	Artificial Neural Network for Malaysia Sample	331
Appendix 3a	Model 1 (3-year prior to bankruptcy sample)	331
Appendix 3b	Model 2 (3-year prior to bankruptcy sample)	334
Appendix 3c	Model 3 (3-year prior to bankruptcy sample)	336
Appendix 3d	Model 1 (2-year prior to bankruptcy sample)	339
Appendix 3e	Model 2 (2-year prior to bankruptcy sample)	341
Appendix 3f	Model 3 (2-year prior to bankruptcy sample)	343
Appendix 3g	Model 1 (1-year prior to bankruptcy sample)	346
Appendix 3h	Model 2 (1-year prior to bankruptcy sample)	348
Appendix 3i	Model 3 (1-year prior to bankruptcy sample)	352
Appendix 4	Logistic regression Nigerian samples	353
Appendix 5a	3-year prior to bankruptcy sample endogeneity test	369
Appendix 5b	2-year prior to bankruptcy sample endogeneity test	376
Appendix 5c	1-year prior to bankruptcy sample endogeneity test	383
Appendix 6	Artificial Neural Network for Malaysia Sample	390
Appendix 6a	Model 1 (3-year prior to bankruptcy sample)	390
Appendix 6b	Model 2 (3-year prior to bankruptcy sample)	392
Appendix 6c	Model 3 (3-year prior to bankruptcy sample)	395
Appendix 6d	Model 1 (2-year prior to bankruptcy sample)	397
Appendix 6e	Model 2 (2-year prior to bankruptcy sample)	399
Appendix 6f	Model 3 (2-year prior to bankruptcy sample)	401
Appendix 6g	Model 1 (1-year prior to bankruptcy sample)	404
Appendix 6h	Model 2 (1-year prior to bankruptcy sample)	406
Appendix 6i	Model 3 (1-year prior to bankruptcy sample)	408

LIST OF ABBREVIATIONS

ACCA	Association of Chartered Certified Accountants
ANN	Artificial Neural Network
APEC	Asia-Pacific Economic Cooperation
ASEAN	Association of Southeast Asian Nations
AUC	Area Under the Curve
BPNN	Back-Propagation Neural Networks
CAC	Corporate Affairs Commission
CAMEL	Capital, asset, management, equity and liquidity
CBN	Central Bank of Nigeria
CCM	Companies Commission of Malaysia
CPI	Consumer Price Index
DOSM	Department of Statistics Malaysia
GDP	Gross Domestic Product
LDA	Linear discriminant analysis
MAMPU	Malaysian Administrative Modernisation and Management Planning Unit
MATRADE	Malaysian External Trade Development Corporation
MCCG	Malaysian Code on Corporate Governance
MDA	Multiple Discriminant Analysis
MITI	Ministry of International Trade and Industry
MM	Modigliani and Miller
MLP	Multilayer Perceptron
MSMEDF	Micro, Small and Medium Enterprises Development Funds
NBS	National Bureau of Statistics Nigeria
NCCG	Nigerian Code on Corporate Governance
NEDEP	National Enterprise Development Program
NID	Neural Interpretation Diagram
NSDC	National SME Development Council
SMEs	Small and Medium-size Enterprises
SMECGS	Small and Medium Enterprises Credit Guarantee Scheme
SMEDAN	Small and Medium-size Enterprises Development Agency of Nigeria
SMIEIS	Small and Medium Industries Equity Investments Scheme
SMEWG	Small and Medium Enterprises Working Group
RBT	Resource-based Theory
RMA	Robert Morris Associates
ROC	Receiver Operating Characteristics

CHAPTER 1

INTRODUCTION

1.1 Background of Study

In recent years, small and medium-sized enterprises (SMEs) are viewed as one of the leading contributors to national economic development in the area of creating employment opportunities, developing indigenous skills and technologies, building market competitiveness, and realising a poverty free society (Jahur & Quadir, 2012). More than 95 percent of the established enterprises across the globe are SMEs, contributing approximately 60 percent of the private sector manpower (Ayyagari, Demirgüç-Kunt & Maksimovic, 2011).

SMEs play a significant role in driving the growth of gross domestic products (GDP) and sustaining employment (Leung & Rispoli, 2011). In the US, Germany, UK, and France, SMEs contribute approximately 51 to 56 percent of the countries' GDP (Association of Chartered Certified Accountants (ACCA), 2013). SMEs in the Association of Southeast Asian Nations (ASEAN) region make up 96 percent of all enterprises, with a 50 to 95 and 30 to 53 percent of contribution to domestic employment and GDP, respectively (SME Corp Malaysia, 2013). For example, Malaysia, as an ASEAN member, SMEs' contribution to GDP is 35.9 percent. However, in Ghana, SMEs are considered to be significant to the local economy, accounting for 90 percent of the businesses and contributing 49 percent to the GDP in 2012 (PricewaterhouseCoopers (PWC), 2013). SMEs' contribution in Nigeria is about 48.7 percent of GDP in terms of nominal value (Agusto & Co., 2016; Nnabugwu, 2015).

Figure 1.1 shows the SMEs' contribution to employment in different country groups which includes, the lower-income countries (Cambodia, Bangladesh, Kenya); lower middle-income countries (Paraguay, Nigeria, Ghana); upper middle-income countries (Brazil, South Africa, Malaysia) and high-income countries (US, UK, France) (World Bank, 2015)¹. Note that on average in all groups (low-income, lower middle-income, upper middle-income and high-income countries), SMEs contribute more than 58 percent of the total employment. As such, SMEs are the key contributors of employment across the globe.



Figure 1.1
Contribution of SMEs to employment, (Dalberg, 2011)

In general, the contribution of SMEs has triggered state and regional initiatives to further strengthen the growth of small businesses around the globe (EU Annual Report, 2013). In Europe, for example, SMEs development is supported by initiatives designed to further innovation, improve access to finance, and provide

¹ For each group, 3 countries are provided as example. For the full list of the countries by groups, refer to <http://data.worldbank.org/income-level/UMC>

business support facilities in the region (Leung & Rispoli, 2011). Asia-Pacific Economic Cooperation (APEC) has also backed a four-year Small and Medium Enterprises Working Group (SMEWG) Strategic Plan (2013 – 2016) with the aim of addressing issues and concerns related to SMEs progress and development, particularly in the financing, management capability, market access, structure and internationalisation of SMEs (Ortecho & Bengoa, 2014).

Despite these initiatives, the failure rate of SMEs is relatively high. For example in Malaysia, an approximately 60 percent failure rate among SMEs has been reported (Ahmad & Seet, 2009). In the UK, approximately 65 percent of the small businesses remain in business after the first three years of initial start-up, but after five years less than 45 percent of the businesses have actually survived (Gray, Saunders & Goregaokar, 2012). Australia also records a high failure rate with 62 percent of the SMEs failing after the third year of operations, while 74 percent fail after the fifth year of operations (Chancharat, 2011). In Nigeria, between 60 to 70 percent of Nigerian SMEs fail in the first three-years of the business operations (Akingbolu, 2010). Likewise in South Africa, 63 percent of the small businesses fail to pass the second year of operations (Cant & Wiid, 2013).

In Malaysia, studies on business failure prediction mainly seek evidence from public listed firms (see Abdullah, Ahmad & Md. Rus, 2008; Halim, Mohd, Rizal & Marzuki, 2008; Md-Rus, Mohd, Abdul Latif, & Nadakkavil, 2013; Mohd Noor & Mohd Iskandar, 2012; Norfian, 2013; Sulaiman, 2001; Zulkarnian, 2006; Zulkarnian, Ali, Md. Nasir, & Mohamad, 2001) because of the easy access to these firm's financial and non-financial information. On the other hand, it is more

challenging to have adequate access to SMEs financial and non-financial information, and thus empirical evidence on SME business failure prediction models is still limited in Malaysia. As for Nigeria, as far as is known, no study has developed a failure prediction model to examine the indicators that could potentially lead to the SMEs failure. Moreover, previous studies on predicting SMEs failure revolve around financial and non-financial indicators (see Abdullah et al. 2014; Karim & Suhaimi, 2013) with limited studies utilising governance indicators (see Ciampi, 2015). A considerable number of studies have incorporated non-financial and governance variables in the business failure prediction models of public listed firms, but evidence from SMEs is still lacking. As such there is still need to further investigate on the cause of SMEs failure in Malaysia and Nigeria as the financial stability and going concern of a company are important considerations for company's stakeholders, including the shareholders, financial institutions, suppliers, employees, government, customers, and society in general. This is because the consequences of business failure have a far-reaching impact on the stakeholders. Therefore, continuous tracking of a company's potential business failure would be a significant concern to the corporate sector and economy.

This research proposes to develop business failure prediction models using a sample of manufacturing SMEs from Malaysia and Nigeria. Malaysia and Nigeria² have a strategic partnership on SMEs development. In 2010, the Central Bank of Malaysia

² "Malaysia and Nigeria are both member of Alliance for Financial Inclusion (AFI). Malaysia joined the institution on May, 2009 while Nigeria joined on March, 2010. AFI was founded in 2008 as the first global knowledge sharing network designed exclusively for financial inclusion policymakers from developing countries. AFI through SME Finance Working Group (SMEFWG) aims to contribute to the development and sustainability of SMEs in developing and emerging countries". For more detail on AFI, refer to <http://www.afi-global.org/about-us>

(Bank Negara Malaysia) and Central Bank of Nigeria signed a memorandum of understanding (MOU) *“to share expertise and exchange relevant information in the areas of SMEs development and policies which includes stimulation of economic development through financing SMEs, effective supervisory framework, increasing productivity, innovation and technology sharing to strengthen the long term competitiveness of the SMEs in Nigeria”* (Central Bank of Nigeria, 2010).

The Nigerian government sees Malaysia as a developing country that has successfully achieved widely acknowledged economic reforms since the Asian financial crisis in the 1990, in the areas of SMEs reforms, microfinance, Islamic finance, development finance institutions, banking supervision, monetary policy, foreign exchange administration, external reserve management, leadership development, performance management and corporate strategy and talent management (Central Bank of Nigeria, 2010). This strategic partnership provides a natural platform for this research to make a comparative study of predicted potential business failure of SMEs in Malaysia and Nigeria. Furthermore, for both countries, the manufacturing sector is among the major drivers of economic growth and development. In Malaysia, there are 47,698 SMEs in the manufacturing sector, representing 5.3 percent of the total SMEs (DOSM, 2016) while in Nigeria, there are 13,990 SMEs in the manufacturing sector representing 19.5 percent (NBS, 2013).

1.2 SMEs in Malaysia

In Malaysia, SMEs plays a vital role in supporting endogenous sources of growth and establishing the infrastructure for faster economic expansion and development (Ortecho & Bengoa, 2014). The interdependency of SMEs and large establishments in collaborating with one another has triggered more development of SMEs in Malaysia (SME Annual Report, 2014/2015). The categorization of SMEs used in this research follows the definition provided by the National SME Development Council (NSDC) of Malaysia as follows: (1) a firm in the manufacturing sector with sales turnover of less than RM50 million (USD 14.12 million³) or full-time employees less than 200 (SME Corporation, 2013). A firm will be considered as a SME if it meets either one of the two specified qualifying criteria specifically the sales turnover or number of employees, whichever is lower. A more detailed definition for manufacturing sector is presented in Table 1.1.

Table 1.1
Definition of SMEs Manufacturing Sector in Malaysia

Category	Employment	Sales turnover (MYR)	Sales turnover (USD) (millions)
Micro enterprises	Less than 5	Less than 300,000	Less than 0.732
Small enterprises	5 – 75	300,000 to less than 15 million	0.732 to less than 3.66
Medium enterprises	75 – 200	15 million to less than 50 million	3.66 to less than 12.20

The Department of Statistics Malaysia (DOSM) highlights that in 2016, SMEs accounted for 98.5 percent of total business formations (or 907,065 businesses) (DOSM, 2016; World Bank, 2016). Most of the businesses are dealing in textiles,

³The exchange rate used for the conversion of MYR to USD throughout the study is 1 USD: 4.1006 MYR, quoted as at 24th September, 2017 refer to <http://www.xe.com/currencyconverter/convert/?Amount=1&From=MYR&To=USD>

and food products, are restaurants and accommodations, as well as are involved with the wholesale and retail trade. In fact, the contribution of SMEs to the GDP growth has progressively outperformed the growth of the national economy since 2004. Figure 1.2 show that SMEs annual growth rate was 5.2 percent in 2016 while the overall economic growth stood at 4.2 percent (SME Corporation, 2015/2016). These growth rates are driven by consumption and investment activities in the domestic market (SME Annual Report, 2015/2016).

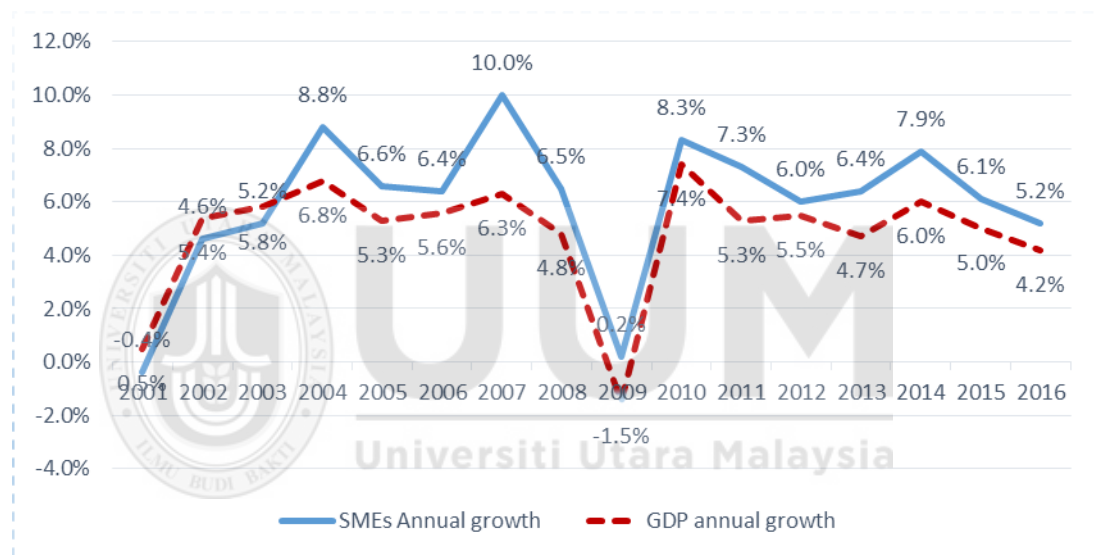


Figure 1.2
SMEs' Contribution to GDP Growth from 2001 to 2016, (SME Corp., 2015/2016)

Figure 1.3 compares the contribution made by large firms and SMEs in proportion to the overall GDP. SMEs' contribution to GDP has grown by 14.4 percent from 2010 to 2016. However, the contribution of large firms to GDP has decreased by 6.8 percent in the same period.

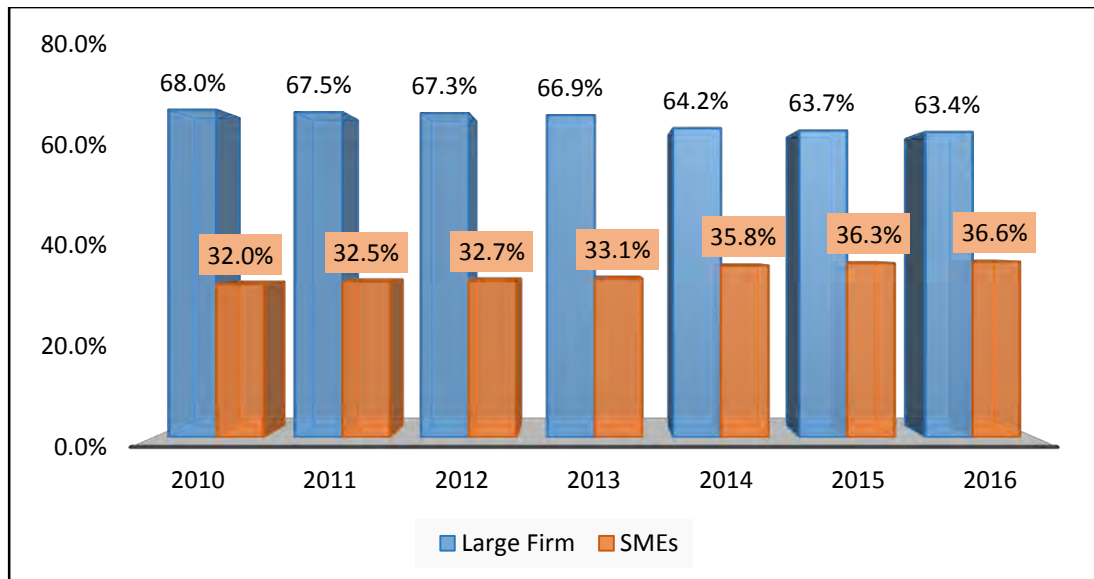


Figure 1.3

Comparison of SMEs and Large Firms' Contributions to GDP (DOSM, 2016)

Supported by the Malaysian government's initiatives and efforts, SMEs development has progressed over one decade, with contribution to GDP increasing from 29.4 percent in 2005 to 36.6 percent in 2016. Some of the key initiatives by the National SME Development Council (NSDC) is the SME Masterplan 2012 to 2020 released in 2012. The government of Malaysia is determined to strengthen the position of SMEs development by setting a stage for a comprehensive approach which will provide a supportive and conducive ecosystem via the SME Masterplan to enhance the contribution of SMEs to the economy (NSDC, 2013). A total of RM6.7 billion has been allocated for SME development during the tabling of the 2017 Budget. The government has further announced tax incentives for SMEs through a reduction in the corporate tax rate with a special rate of 18 percent. The government announced additional funds of RM 70 million, mainly to continue supporting the long-term development agenda through the implementation of the SME Masterplan and other supporting initiatives especially the ones that encourage business formations through acculturation of entrepreneurship among the youth and

women. These measures were also intended to raise the productivity of SMEs by encouraging a shift towards automation and mechanisation (SME Corp, 2017).

Another initiative by the government to stimulate SMEs growth is the Going-Export Programme (HIP 4) to internationalise export ready SMEs, which is managed by the Malaysian External Trade Development Corporation (MATRADE). The initiative has so far benefited 71 companies with two companies securing sales contract amounting to more than RM1.8 million. The Malaysian government initially began with 20 SMEs in the BioNext segment, while the project on HIP 1, led by the Malaysian Administrative Modernisation and Management Planning Unit (MAMPU), has focused on ease of doing business towards creating a single gateway for business registration and licensing (SME Annual Report, 2014/2015).

Furthermore, the Ministry of International Trade and Industry (MITI) through its agency, MATRADE introduced an initiative called Market Development Grant (MDG). The initiative aims to render support in the form of reimbursable grants to exporters for SMEs, trade and industry associations, service providers, chambers of commerce, as well as professional bodies to venture into the export market by participating in export promotional activities. As at 2015, MATRADE had allocated RM30.7 million under the initiative to assist 3,386 SMEs to export their products and services (SME Annual Report, 2015/2016).

Despite these initiatives, the failure rate of SMEs in Malaysia is relatively high. For example, an approximately 60 percent failure among SMEs has been reported (Ahmad & Seet, 2009). More than 42 percent of the SMEs in the manufacturing

sector that began operations in the year 2000 had ceased operations in 2005 (SME Corp. 2012).

For the purpose of this research, the focus is mainly on Malaysian SMEs in the manufacturing sector. These SMEs account for 96.6 percent (47,698) of total establishments and 34.9 percent (RM191.6 billion or USD54.12 billion) of total output in the manufacturing sector (SME Annual Report, 2016/2017). The SMEs in this sector are mainly involved in manufacturing wearing apparels, food products, reproduction of recorded media and fabricated metals and printing (refer to Figure 1.4).

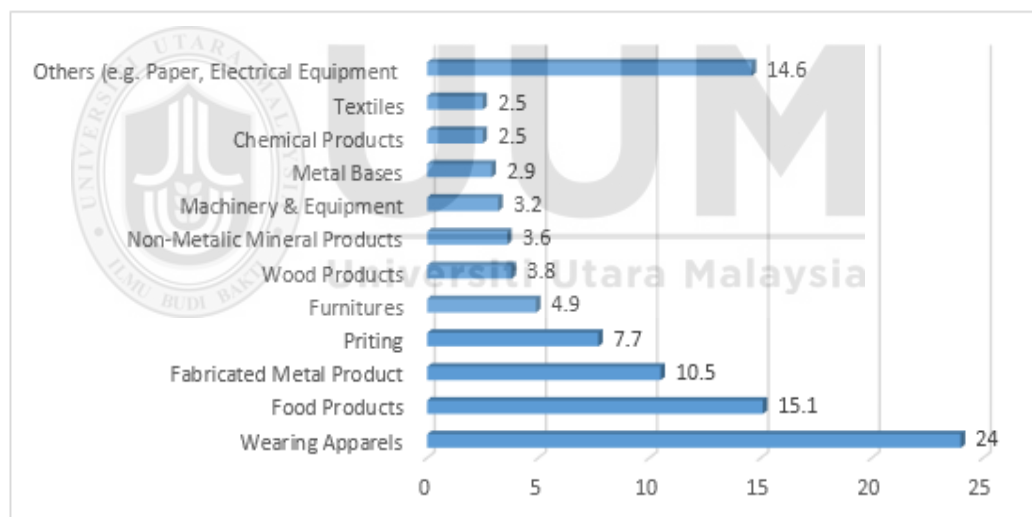


Figure 1.4
Proportion of SMEs by the Manufacturing Subsectors, (DOSM, 2016)

1.3 SMEs in Nigeria

In an emerging market like Nigeria, SMEs play an important role in reengineering the socio-economic landscape of the country. These enterprises signify a phase in industrial evolution from traditional to modern technology. SMEs hold the key to the sustainable business and economic development of the Nigerian economy

because SMEs are the source of new indigenous technological innovations, new products and job creation (Anthony, 2014). The National Bureau of Statistics Nigeria (NBS) and the Small and Medium Enterprises Development Agency of Nigeria (SMEDAN) report that SMEs in Nigeria account for 97 percent of the total business formations in the country and contribute 87.9 percent of the workforce in addition to 48 percent of industrial output in terms of value added (Kadiri, 2012; Olukayode & Somoye, 2013).

The National Policy on SMEs defines Nigerian SMEs into three categories (refer Table 1.2), namely micro, small and medium enterprises. These SMEs are defined based on the number of employees and total assets in Nigerian currency (NGN), excluding land and building.

Table 1.2
Definition of SMEs in Nigeria

Category	Employment	Assets (NGN ³ millions) (excluding land and building)	Asset in USD ⁴ (millions)
Micro enterprises	Less than 10	Less than 10	Less than 0.067
Small enterprises	10 – 49	10 to less than 100	0.029 to less than 0.286
Medium enterprises	50 – 199	100 to less than 1000	0.286 to less than 2.86

Note: Adapted from Small and Medium Enterprise Development Agency of Nigeria (SMEDAN, 2003).

Recognising the potential of SMEs, various measures, policies and programmes have been designed and implemented by the government to stimulate SMEs

⁴ The exchange rate used for the conversion of NGN to USD throughout the study is 1 USD: 350.050 NGN, quoted as at 24th September, 2017 refer to <http://www.xe.com/currencyconverter/convert/?Amount=1&From=MYR&To=USD>

development to become a more vibrant contributor of the Nigerian economy. SMEDAN is the main support system and policymaker of the SMEs. To improve SMEs' access to financing, the CBN approved a total of NGN 500 billion (USD 3.3 billion) debenture stock in 2010 issued by the Bank of Industry (BOI). Sixty percent of the debenture stock (NGN 300 billion) was utilised in power projects and NGN 200 billion (USD 1.3 billion) was used for the refinancing or restructuring of banks' existing loan portfolios to Nigerian SMEs in the manufacturing sector (CBN Bulletin, 2015). The objective of the allocated funds, which were used to refinance the loans, was to fast-track the development of the SMEs in the manufacturing sector of the Nigerian economy and improve the financial position of the deposit money banks (CBN Bulletin, 2015).

Complimentary to the above initiative, the BOI has also established a NGN200 billion (USD 1.3 billion) Small and Medium Enterprises Credit Guarantee Scheme (SMECGS), for encouraging access to loans by SMEs in Nigeria. The purpose of the SMECGS is to provide assurances for loans from banks to SMEs and manufacturers; increase the access of promoters of SMEs and manufacturers to loans and set the pace for industrialization of the Nigerian economy (CBN Bulletin, 2015). The overall goals of the refinancing of bank loans and SMECGS to SMEs was to generate employment, increase output, diversify the revenue base, provide inputs for the industrial sector and increase foreign exchange earnings.

The Nigerian government also approved the recapitalisation of BOI, a development-centred finance institution which assists SMEs with financial constraints by tripling the bank's total capital from USD1.57 billion to USD4.72 billion (ACCA, 2013).

Additionally in 2013, the government introduced the Micro, Small and Medium Enterprises Development Funds (MSMEDF) with the purpose of channelling low interest funds to the SMEs sub-sector by providing facilities to qualify and eligible participating financial institutions. As of December 2014, over 158,700 SMEs have been issued loans at a single digit rate through the BOI (SMEDAN, 2014). Furthermore, commercial banks are required to set aside 10 percent of their profits before tax as an additional source of funding for SMEs under the Small and Medium Industries Equity Investments Scheme (SMIEIS), (SMEDAN, 2013).

However, despite these initiatives by the government, the failure rate of SMEs in Nigeria is high. Studies have shown that the majority of the Nigerian SMEs fail to survive beyond the first five-years of existence, with a survival rate of only 5 to 15 percent (Anthony, 2005). Additionally, between 60 to 70 percent of Nigerian SMEs fail in the first three-years of their operations (Akingbolu, 2010).

SMEs are important to the development growth of any economy as they hold great potentials for output diversification, employment generation, development of indigenous entrepreneurship, improvement of local technology and forward integration with large-scale industries. There has been an under performance of the SMEs sub-sector and this has weakened its impact to economic growth and development in Nigeria.

The contribution of Nigerian SMEs to GDP is inconsistent. In 2009, SMEs contributed 37 percent to GDP (Nwannekanma, 2009), while this contribution increased to 46.5 percent in 2010 (National Bureau of Statistics (NBS), 2010;

SMEDAN, 2010), but fell to 10 percent in 2013 (ACCA, 2013). However, recent data reported that SMEs contribute 48.7 percent to the country's GDP in terms of nominal value (Agusto & Co., 2016; Nnabugwu, 2015) with the manufacturing SMEs contributing 30 percent of the country's total export (ACCA, 2013). The manufacturing sector of SMEs is identified as one of the contributors in achieving the Nigerian nation's vision of 20-2020⁵.

1.4 Problem Statement

Issues on predicting business failure have stimulated the interest of researchers. Studies by Altman and Sabato (2007), Altman, Sabato and Wilson (2010), Blum (1974), Edmister (1972), Keasey and Watson (1987), Lussier (1995), Platt and Platt (1990), and Zmijewski (1984) are just some among others that have contributed to the literature on business failure of small firms in developed countries. Since then a number of models have been proposed to improve the accuracy rate of business failure prediction models of SMEs. Nonetheless, most of the existing literature mainly seeks evidence from the developed countries. Therefore, there is still room for contribution to the literature on predicting business failure with evidence from developing countries such as Malaysia and Nigeria.

SMEs in both countries pose relatively high failure rates regardless of government initiatives (see Ahmad & Seet, 2009; Akingbolu, 2010; Anthony, 2005; Gunto &

⁵ "Vision 20-2020 aims to position Nigeria as one of the top 20 economies in the world with GDP of not less than USD900 billion and per capita income of not less than USD4000/annum by the year 2020. The vision aims to stimulate Nigeria's economic growth onto a path of sustained and rapid socio-economic development. The vision also aims to transform the manufacturing sector of Nigeria into a vibrant and globally competitive sector that contributes significantly to the GDP, with a manufacturing value added of not less than 40 percent" (Accenture, 2009).

Haji, 2013; SME Corporation, 2012). Though SME reforms in Malaysia are deemed successful, as evidenced by the increasing contribution to GDP since 2010 (see Figure 1.3), the failure rate of SMEs has been increasing at an average rate of 60 percent (Ahmad & Seet, 2009). Moreover, the SME Corporation (2012) reports that about 42 percent of the SMEs in the manufacturing sector that began operation in the year 2000 had ceased operations in 2005.

Similarly, studies show that majority of the Nigerian SMEs fail to survive beyond the first five-years of their existence, with a survival rate of only 5 to 15 percent (Anthony, 2005). Another study reveals that 60 to 70 percent of Nigerian SMEs fail in the first three-years of the operations (Akingbolu, 2010). In addition, the contribution to the country's GDP between 2010 and 2014 was not stable (Agusto & Co., 2016; NBS, 2010; Nnabugwu, 2015; SMEDAN, 2010). Nigeria ranked 131 out of 185 countries in a survey on the ease of doing business by Delta Economics (World Bank, 2014). This suggests that emerging economies like Nigeria face substantial challenges in creating sustainable environments for SMEs.

In Malaysia, studies on business failure prediction mainly seek evidence from public listed firms (see Abdullah, Ahmad & Md. Rus, 2008; Halim, Mohd, Rizal & Marzuki, 2008; Md-Rus, Taufil Mohd, Abdul Latif, & Nadakkavil, 2013; Mohd Noor & Mohd Iskandar, 2012; Norfian, 2013; Sulaiman, 2001; Zulkarnian, 2006; Zulkarnian, Ali, Md. Nasir, & Mohamad, 2001) because of the easy access to these firm's financial and non-financial information. On the other hand, it is more challenging to have adequate access to SMEs financial and non-financial information, and thus empirical evidence on SME business failure prediction models

is still limited in Malaysia. As for Nigeria, as far as is known, no study has developed a failure prediction model to examine the indicators that could potentially lead to the SMEs failure. Moreover, previous studies on predicting SMEs failure revolve around financial and non-financial indicators (see Abdullah et al. 2014; Karim & Suhaimi, 2013) with limited studies utilising governance indicators (see Ciampi, 2015). A considerable number of studies have incorporated non-financial and governance variables in the business failure prediction models of public listed firms, but evidence from SMEs is still lacking.

The limited evidence available would seem to suggest that the underlying causes of business failure among SMEs in Malaysia and Nigeria are numerous, and any stakeholder concerned in attempting to forecast which companies are vulnerable will have to depend on a broad information set on which to base his/her predictions. This will consist of corporate governance, industry specific information, macroeconomic lead indicators and quality of management, as well as financial ratios relating to a particular company which are expected to enrich understanding of SMEs failure. Although SMEs are not publicly listed companies, there is a global concern to encourage corporate governance, such as board and ownership structures of SMEs due to the high failure rate of small businesses around the world (Headd, 2003).

Previous studies that have incorporated governance variables in their SMEs' business failure prediction models are found to perform relatively better in comparison to models with just financial and non-financial indicators (Abdullah, Ma'aji & Khaw, 2016; Ciampi, 2015). These governance indicators, such as number

of directors, controlling shareholders, gender of managing director, independent directors, CEO duality, among others have shown a significant contribution in the development of a higher predictive SMEs failure prediction model (Abdullah et al. 2016; Ciampi, 2015). Furthermore, a business failure prediction model should incorporate the external environment such as the changes of interest rates, inflation rate, and economic conditions (Zavgren, 1983). These macroeconomic indicators could be relevant explanatory factors to explain SMEs failure because the changes in the macroeconomic environment may exacerbate or mitigate the impact of firm specific variables on business failure (Hu & Sathye, 2015).

A number of models have been proposed to correctly predict corporate failure using different statistical methods which include the logit regression model, univariate analysis, hazard model, multiple discriminant analysis (MDA), artificial neural networks (ANN) and probit model. However, evidence on the application of these statistical methods among small businesses is still limited in the existing literature. Each statistical method has its own advantages and disadvantages associated to their application to the topic of business failure prediction (Ohlson 1980; Platt & Platt 1990; Zavgren, 1985). For example, MDA assumes the independent variables of the model as multivariate normally distributed, but in practice, this assumption is often violated (Barnes, 1987; Deakin, 1976), which may bias the results of the significance tests and estimated error rates (McLeay & Omar, 2000). The logit model is sensitive to the problem of multicollinearity, thus the inclusion of highly correlated variables should be avoided (Ooghe et al., 1993; Doumpos & Zopoudinis, 1999). ANN on the other hand can better deal with missing data, outliers, and multicollinearity than regression (Elliot & Kennedy, 1988). Accordingly, further

investigation is required to compare the consistency, predictive accuracy rate and performance of the business failure prediction models developed using different statistical methods.

Motivated by the contexts discussed above, this study will carry out a comparative study to identify the indicators that could predict business failure among Malaysian and Nigerian SMEs in the manufacturing sector. This study will further probe into the financial, non-financial, corporate governance and macroeconomic indicators by comparing the accuracy rate of the logit model and ANN.

1.5 Research Questions

The main question to be answered in this research is, “what are the indicators that could predict business failure among Malaysian and Nigerian SMEs in the manufacturing sector using the logit model and ANN?” Specifically, the research questions are as follows:

1. What are the financial, non-financial, corporate governance and macroeconomic indicators that could predict business failure among SMEs in Malaysia and Nigeria?
2. Will the predicted indicators remain consistent when different statistical techniques are used to develop the business failure prediction models for the SMEs in Malaysia and Nigeria?
3. Which statistical technique, logit model or ANN, provides a higher accuracy rate in predicting SMEs failure in Malaysia and Nigeria?

1.6 Research Objectives

The general objective of this research is to identify indicators that could predict business failure of Malaysian and Nigerian SMEs in the manufacturing sector using the logit model and ANN. Specifically, the objectives are as follows:

1. To examine the financial, non-financial, corporate governance and macroeconomic indicators in predicting business failure among SMEs in Malaysia and Nigeria.
2. To compare the consistency of the business failure prediction models developed using different statistical techniques for the SMEs in Malaysia and Nigeria.
3. To identify which statistical technique, logit model or ANN, provides a higher accuracy rate in predicting SMEs failure in Malaysia and Nigeria.

1.7 Significance of study

Predicting business failure of SMEs is important to sustainable economic development. SMEs business failure affects various stakeholders, such as the management of SMEs, employees, shareholders, government, financial institutions and trade creditors. SMEs are one of the major contributors of employment and economic development in Malaysia and Nigeria. Therefore, relatively high business failure among SMEs will bring negative consequences to the economic development of both countries. Some of these consequences include high unemployment rate (Sullivan, Warren & Westbrook, 1998); less income to the country in terms of taxes (Valackiene, 2005); and social problems (Simona, 2008).

The governments of Malaysia and Nigeria have been injecting billions of dollars aimed at revamping and supporting SMEs development through financial support, infrastructure, tax benefits and incentives, ease of doing business and strategic planning through training and development and strategic partnerships (SME Annual Report, 2012/2013; SMEDAN, 2013). Therefore, it is important for both countries to ensure SMEs survival so that the billions of dollars spent by the governments do achieve the desired outcomes as these two countries are experiencing relatively high level of SMEs failure. A comparative investigation of these two countries will provide additional insight on the predictors of business failure since both countries share a strategic partnership in their policy reforms, initiatives, and commitment towards SMEs development.

An effective business failure prediction model can reduce economic losses because the model would enable stakeholders to detect early signals of potential business failure and to take corrective measures prior to the potential failure. For example, the business bankruptcy prediction models developed in this study could be used by the policymakers of Malaysia and Nigeria, such as NSDC and SMEDAN respectively, to assess the well-being of the SME before deciding on any form of assistance for their sustainability and continuous development. Furthermore, understanding the external causes of business bankruptcy would allow policymakers to better serve the business sector.

Many studies argue that some of the major reasons that leads to SME bankruptcy is inefficiency in utilising their assets, insufficient working capital and poor debt management (Anthony & Harry, 2014; Cant & Wiid, 2013; Chancharat, 2011). The

outcome of this study could serve as an early warning signal for the management of SMEs so as to address and to take proactive measures to prevent the businesses from failure. The outcome could be used to guide managerial action towards identifying the significant factors that are likely to cause potential bankruptcy of their companies. The finding of this study could assist the management of SMEs to understand the characteristics of financial ratios that have the likelihood of putting their firm into potential bankruptcy. This will assist the management to implement timely solutions that would enable the SME to develop viable financial strategies to avoid going bankrupt.

In addition, the output of this study could assist creditors, such as the commercial banks, to assess the potential failure of an SME prior to deciding whether to offer new or additional funding. Statistics from the Central Bank of Nigeria (2014), as in figure 1.5, show that commercial banks in Nigeria have reduced the total lending to SMEs due to their high failure rate. Additionally, the banks might be lacking an appropriate model, like the outcome of this study, which could help the banks to assess the going concern of SMEs (Muhammad & Bala, 2013).

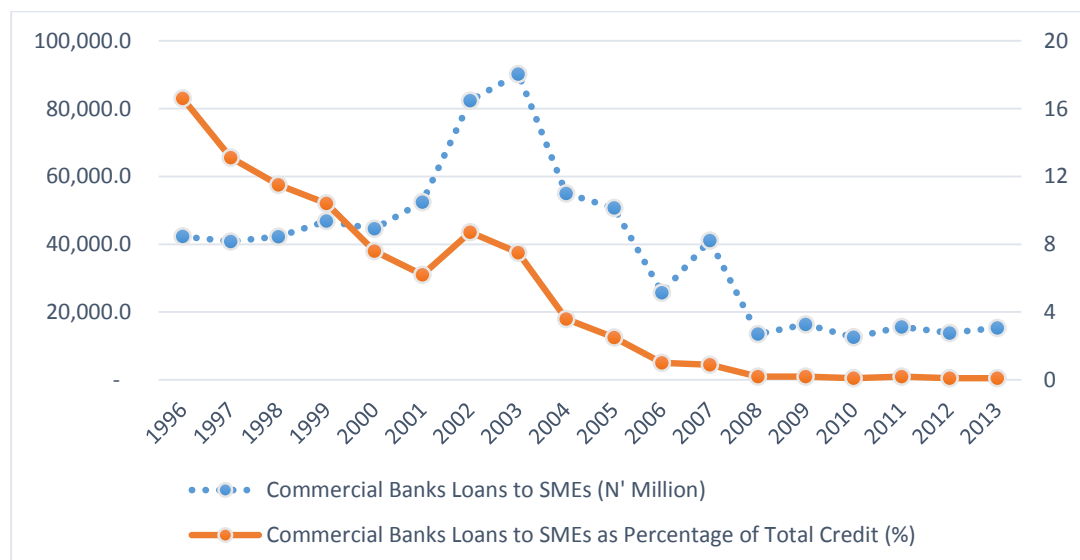


Figure 1.5
Commercial banks loan to SMEs (CBN, 2014)

Furthermore, suppliers who are also considered as close associates or trade creditors to SMEs could also benefit from this study. Previous literature shows that SMEs depend on trade credit as a major source of short term financing (Altman & Sabato, 2007; Behr & Guttler, 2007; Shane, 1996). Therefore, the business failure prediction models developed in this study could provide additional information for these trade creditors to decide on their credit policy towards SMEs given the fact of their high failure rate.

1.8 Scope of the study

This study will predict business failure among manufacturing SMEs in Malaysia and Nigeria using financial, non-financial, governance and macroeconomic indicators. The models developed in this study could serve as early warning signals as they predict business failure as early as three, two and one year prior to failure. The observation period covered is from 2000 to 2014.

The study focuses mainly on the small and medium-sized (SMEs) because of the availability of data. The SMEs in Malaysia are defined in table 1.1 as having a total sales turnover of around USD 0.073 million to USD 3.66 million and USD 3.66 million to USD 12.20 million respectively (SME Corp., 2013). While in Nigeria the small and medium-sized SMEs are defined as having a total assets of USD 0.028 million to USD 0.286 million and USD 0.286 million to USD 2.86 million respectively. Though the micro category constitutes the largest proportion of SMEs in Malaysia (see Figure 1.6) as well as Nigeria, the exclusion of this group is due to

difficulty in accessing their financial and non-financial data as a lot of their data is missing.

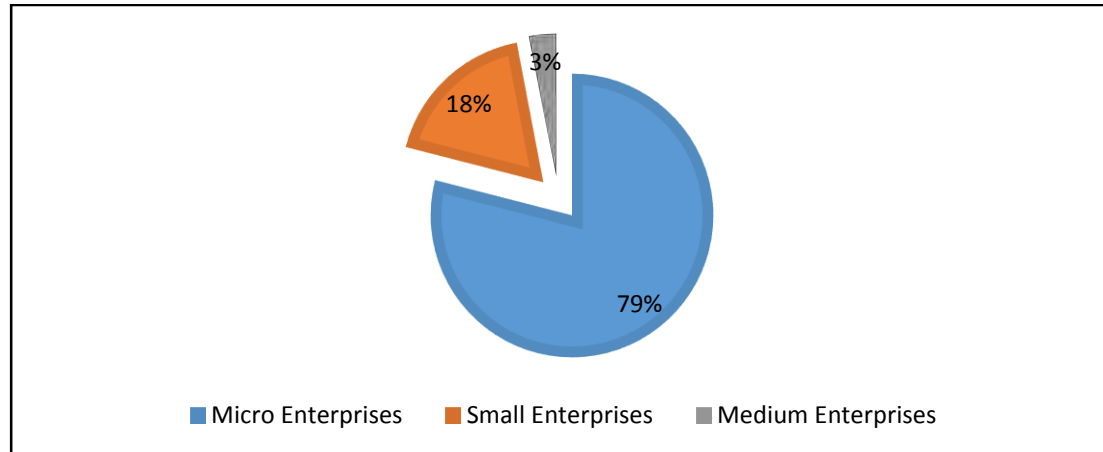


Figure 1.6
Percentage Share of SMEs Categories in Malaysia (DOSM, 2011)

1.9 Organisation of the Study

The study is organised into five chapters. The first chapter is the introductory chapter that covers the background to the study, reviewing the performances of SMEs in a global perspective as well as Malaysia and Nigeria. The chapter will then continue with the problems statement and the purpose of the study, research questions, and significance of the study, the scope as well as the structure of thesis. Chapter 2 outlines the underlying theories and empirical evidence on financially distressed SMEs relating to the development of financial distress models based on financial and non-financial distress models. This chapter is sub-divided into three sections: firstly, underlying theories, secondly empirical evidence on financially distressed SMEs based on financial, non-financial and governance variables distressed models; and thirdly, default prediction methods. Chapter 3 discusses the methodology to determine the SMEs failure. This chapter describes the data and method used to fulfil the objective of this study.

Chapter 4 presents the results of the empirical finding on the indicators that could predict business failure of Malaysian and Nigerian SMEs in the manufacturing sector using the logit model and ANN. The chapter further identifies the accuracy rate in predicting SMEs failure and compare on the consistency of the business failure prediction models developed using the different statistical techniques for the SMEs in Malaysia and Nigeria. Finally, chapter 5 provides an overall summary and concludes the study. The implications, limitations and recommendations for future research are discussed in this final chapter.



CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of the related underlying theories, existing empirical literature on SMEs' business failure, and the commonly used statistical methods to predict business failure.

2.2 The Underlying Theories

Though researchers agree that the construction of a stable and more scientific failure prediction model requires theoretical support (Neophytou, Charitou and Charalambous, 2001), still there is lack of general theory of business failure that is relevant to distinguish between surviving and failing firms (Dimitras et al. (1996). Therefore, the selection of business failure predictors is subject to the popularity and predictive power of each predictor in previous studies (Dirickx & Van Landeghem, 1994; Karels & Prakash, 1987).

In the absence of a well-established theoretical framework, this study builds on the underlying theories related to capital structure to justify the selection of variables used to predict SMEs' failure. Bismark and Pasaribu (2012) also addresses the theoretical foundations of corporate failure using the neo-classical theory of capital structure aiming to demonstrate the feasibility of such approach. The theories include; the Modigliani and Miller (MM) propositions, trade-off theory, pecking order theory, agency theory and stewardship theory.

2.2.1 Modigliani and Miller (MM)

Miller and Modigliani's (1958) proposition I suggest that a company's value remains the same at all levels of gearing, indicating that no optimal capital structure exists for a specific company. Therefore capital structure is irrelevant to the value of the firm. They argue that in a perfect world, where there are no transaction cost and no taxes, the market value of a company depends on its expected performance that is the number of available positive net present value (NPV) projects at its disposal. When bankruptcy risk is ignored, a distress company could always raise additional fund since it would not have any impact on the firm's value.



Figure 2.1
Modigliani and Miller (MM) Proposition I

Figure 2.1 show the first proposition of Modigliani and Miller (1958), where it illustrates that the value of the firm remains the same regardless of the debt and the equity ratio in the capital structure. However, MM proposition I has led to an interesting debate on financing mix. Studies indicate that Modigliani and Miller (1958) proposition I fails, if taxes, bankruptcy cost and transaction cost are taken into consideration.

Modigliani and Miller (1963) extend their argument to recognise corporate tax. MM proposition II argues that as company gears up by replacing equity with debt, it shields more and more of its profits from corporate tax. This suggest that the optimal capital structure for a company would be 100 percent debt financing. Moreover, the value of an unlevered firm goes below that of the levered firm by an equal amount of the present value of the tax savings that arise from debt usage.

However, there is problem with MM proposition II since in practice corporations do not adopt an all-debt capital structure. This indicates the existence of factors such as high financial risk which may weaken the tax advantages of debt finance and which MM proposition II fails to take into account. Furthermore, having high level of leverage will also offset the tax benefit enjoyed by the company thereby endangering it to a possible bankruptcy risk due to high level of financial risk.

2.2.2 Trade-off Theory

The optimization of capital structure involves a trade-off between the present value of the tax rebate associated with a marginal increase in leverage and the present value of the marginal cost of the disadvantages of leverage (Robichek & Myers, 1965). Firm's financing mix determines the states in which the firm will have to settle its debt obligation and receive the tax savings attributable to debt financing. The firm's financing mix also determines the states in which the firm is insolvent and incurs bankruptcy penalties (Hirshleifer, 1966; Kraus & Litzenberger, 1973). The reality is that at high levels of gearing, there is possibility a company defaulting on its interest commitments and financial risk of the company will increase substantially. Furthermore, at a higher level of gearing, shareholders would require a

higher rate of return to compensate them for taking up high financial risk (Hirshleifer, 1966; Kraus & Litzenberger, 1973; Robichek & Myers, 1965).

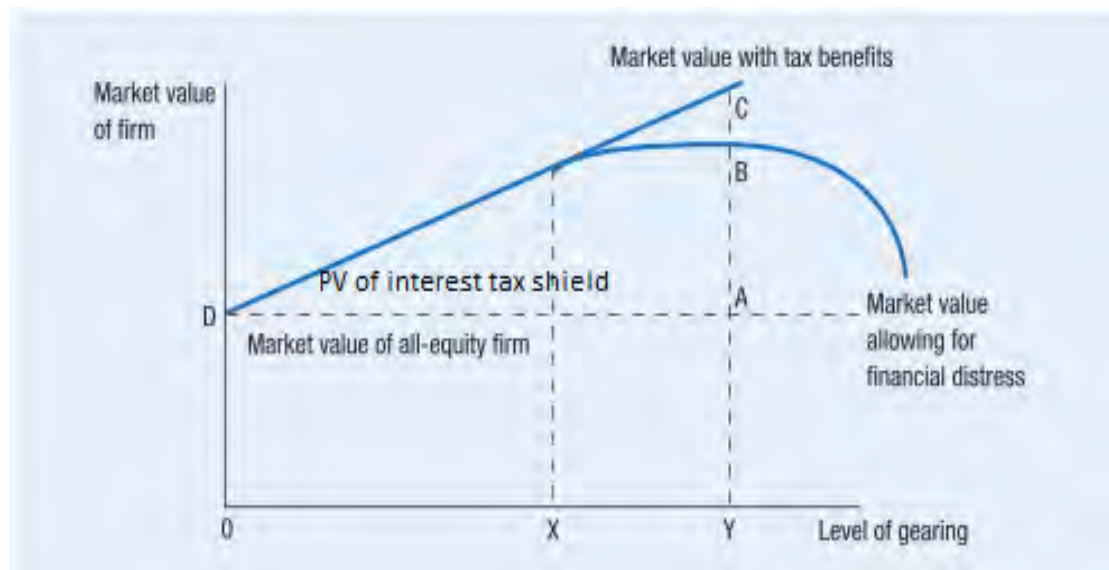


Figure 2.2
Trade off theory (Watson & Head, 2010).

Figure 2.2 shows that when an all-equity firm increases its gearing, the market value of the firm increases due to the increasing value of tax shield. However, when the gearing level increases beyond X, the firm's cost of equity will increase more steeply to compensate the shareholders for the higher bankruptcy risk that outweighs the benefit of tax shield. Beyond gearing level Y, the marginal benefit of tax shield is outweighed by the marginal increase in cost of equity due to higher bankruptcy risk.

An important purpose of the theory is to explain the fact that corporations usually are financed partly with debt and partly with equity. It states that there is an advantage to financing with debt, which is the tax benefits of debt but there is a cost of financing with debt, which includes bankruptcy costs of debt and non-bankruptcy

costs (e.g. staff leaving, suppliers demanding disadvantageous payment terms and bondholders/stockholders conflict). The marginal benefit of debt declines as debt increases, while the marginal cost increases, so that a firm that is optimizing its overall value will focus on this trade-off when choosing how much debt and equity to use for financing.

2.2.3 Pecking Order Theory

Pecking order theory is first suggested by Donaldson (1961), who goes against the idea of companies having a unique combination of debt and equity to minimise the cost of capital. Donaldson (1961) argues that when companies become more profitable, the keenness for external financing reduces since internal funds would be available to execute long-term projects. If only internal finance proves insufficient, bank borrowings and corporate bonds are the preferred source of external financing. The least preferred source of financing is the issuance of new equity. These preferences are subject to the cost of issuance and the ease of accessibility of the sources of financing. Retained earnings are readily accessible with no issuance costs. As for the choice between debt and equity, the cost of issuing debt is lower than the cost of issuing equity. It is also possible to raise small amounts of debt, whereas it is not usually possible to raise small amounts of equity (Donaldson, 1961).

Myers (1984) extends Donaldson's (1961) pecking order theory by postulating that the cost of financing increases with asymmetric information. He suggests that the order of preference stems from the existence of asymmetry of information between the company and the capital markets (Myers, 1984). Pecking order theory starts with

asymmetric information as managers know more about their companies' prospects, risks and value than outside investors. Asymmetric information affects the choice between internal and external financing and between the issue of debt or equity. Therefore, there exists a pecking order for the financing of new projects.

For example, suppose that a company wants to raise fund for its new project and the capital market has underestimated the benefit of the project. The company's managers, with their insider information, will decide to finance the project with retained earnings. This is because retained earnings are the least information sensitive source of financing. However, if retained earnings are insufficient, managers will choose debt financing in preference to issuing new shares, specifically when the equity is undervalued by the market. The issuance of equity would signal a lack of confidence in the board as they feel the share price is overvalued. The market would perceive it negatively which may lead to a drop in share price.

However, in the case of SMEs, the order would relate more to retain earnings and debt finance. This is because majority of the SMEs managers tend to be the business owners and they do not normally want to dilute their ownership claim. Therefore, the theory's application to SMEs implies that external equity finance issues may be inappropriate. Furthermore, since SMEs are not listed in the stock market, the issuance of equity would mostly be then internal equity finance that is among the existing managers (Zoppa & McMahon, 2002). This type of issuance would probably not surrender control.

2.2.4 Agency Theory

Managers have both the ability to commit the organisation to any form of contracts and transactions they deem appropriate as they act on behalf of the business owners. As such there is a need to ensure that the managers' responsibilities are towards protecting the interest of the owners. Agency theory provides a platform upon which this can be ensured. The existence of agency problem is conventionally associated with listed companies. Agency relationship is defined as a contract under which the principal (shareholders) engages the agent (managers) to perform some services on their behalf (Jensen & Meckling, 1976). Agency theory suggest that the agency problem is an essential element of the contractual view of the firm due to the separation of ownership and control. The divergence of interests can result in agency problems between the suppliers of funds, both in terms of equity and debt and the managers (Jensen & Meckling, 1976). Jensen and Meckling (1976) further argue that a company can be viewed as a series of agency relationships between the different interest groups as illustrated in Figure 2.3. In fact, there are two main types of agency problems – agency costs of debt and agency costs of equity.

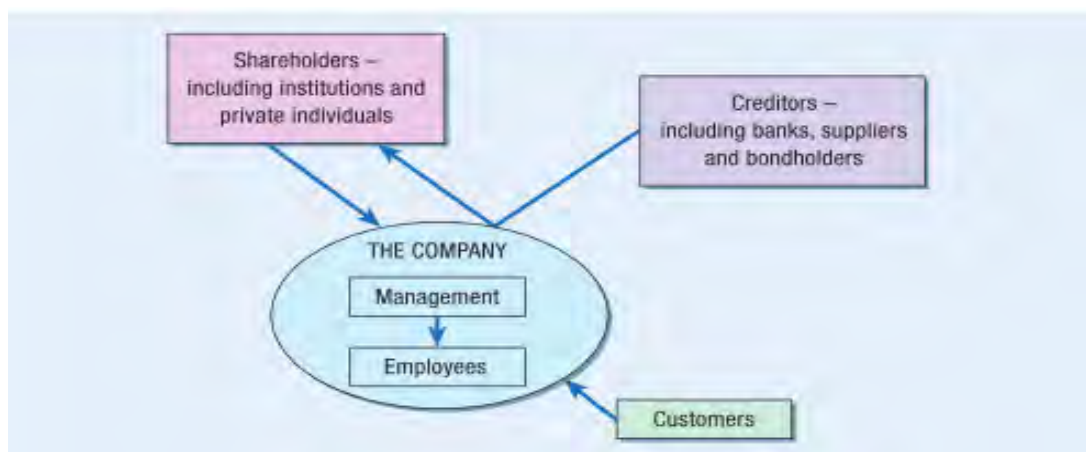


Figure 2.3

The agency relationships in a company (Watson & Head, 2010).

Corporate governance mechanisms, such as presence of non-executive and independent directors and debt, are used in an attempt to reduce this conflict of interest (Grosseman & Hart, 1982; Jensen, 1986). However, introducing debt into the picture creates another potential conflict of interest because there are three parties involved: owners, managers and lenders, each with different goals. Grosseman and Hart (1982) were the first to claim that agents (managers) could pre-commit to work hard to the interest of shareholders by using debt rather than equity. Jensen's (1986) free cash flow theory considers additional debt beneficial since the firm attempts to improve the productivity of its assets as a result of additional debt acquired. The use of debt not only reduces the free cash flow but also provides discipline to management limiting managerial discretion (Jensen, 1986).

Most of the time managers tends to spend free cash flows by increasing the size of the firm through investing in negative NPV projects due to availability of free cash flow. Taking on more debt will likely be the solution for this problem because issuing more debt will increase interest and principal payments hence reduces the availability of free cash flows thereby reducing agency costs. Shleifer and Vishny (1997) provided extensive survey about the role of debt in reducing the conflict of interests between managers and shareholders. They argue that the benefit is usually the reduction in the agency cost, such as preventing the manager from investing in negative net present value projects, or forcing them to sell assets that are worth more in alternative use.

On the other hand, high level of leverage is associated with agency problem such as conflict between shareholders and debt holders. As leverage increases, the usual

agency costs of debt rise, including bankruptcy cost (Jensen, 1986). Furthermore, debt overhang problem is associated with agency cost of debt where firms may forego good projects if they have significant debt outstanding as pointed out by Myers (1977). The reason is that for a firm facing financial distress, a large part of the returns from a good project go to debt holders. The main costs of debt is that firms may be prevented from undertaking good projects because debt covenants hinder them from raising additional funds, or else they may be forced by creditors to liquidate when it is not efficient to do so. Basically, agency cost of debt arises because of different interests between shareholders (represented by managers) and debt holders (Jensen & Meckling, 1976). An agency theory context is relevant in investigating SMEs because agency problems due to information asymmetry between the owner-managers and outside suppliers of funds are more likely to be present in smaller firms than in their larger counterparts due to the requirement of disclosure that is not in SMEs (Myers, 1984; Myers & Majluf, 1984).

As agency theory suggest, when managers' interest are aligned with those of shareholders through ownership, agency problems should not exist, at least not between the owners and managers when ownership and management overlap entirely (Jensen & Meckling, 1976). This applies to small and medium enterprises (SMEs), which are typically characterized as having concentrated ownership structures and overlapping roles of owners and management. SMEs are less likely to face agency conflict between managers and shareholders because they are often of the same entity. However, in a closely held firms, such as family firms, agency conflicts may arise from divergence of interest between the majority and minority owners (Schulze, Lubatkin, & Dino, 2003). Potential agency problem occurs when

managers make decisions that are not consistent with the objective of shareholders' wealth maximisation. If the management's interests diverge from that of the shareholders, in a case where the management and shareholders of SMEs are not of the same entity, the shareholders will have to bear the cost. Management may be tempted to take suboptimal decisions that may not work towards maximizing the value for the firm. Any measures implemented to oversee and to prevent this will have a cost associated with it. Thus, agency costs will include both, the cost due to the suboptimal decision, and the cost incurred in monitoring the management to prevent them from taking such decisions (Jensen & Meckling, 1976).

2.2.5 Stewardship Theory

Unlike agency theory, stewardship theory assumes that managers are stewards whose behaviours are aligned with the objectives of their principals. The theory suggest that stewards will behave in a pro-social manner and behaviour to achieve the interest of the principal and the organization (Davis, Schoorman & Donaldson, 1997; Donaldson & Davis, 1991). The theory argues that managers are not an opportunistic shirker, but a good steward of corporate assets, who are loyal to the company and interested in achieving high performance. Managers are perceived to be motivated by a need to achieve, to gain intrinsic satisfaction through successfully performing inherently challenging work, to exercise responsibility and authority, and thereby to gain recognition from peers and bosses (Davis et al. 1997; Kim, Al-Shammari, Kim, & Lee, 2009).

According to the stewardship theory, presence of CEO duality in an organisation will bring in the benefits of unity of direction and of strong command and control.

Thus, improving performance of the organisation and reducing the likelihood of bankruptcy. CEO duality will enhance effectiveness of the organisation and produce, as a result, superior returns to shareholders than separation of the roles of chair and CEO (Donaldson 1985; Donaldson & Davis, 1991). Accordingly, in the case of CEO-duality in a small firm, the degree of identification between the image of the CEO/chairman and the image of the company tends to be much higher compared to larger companies, which damages the CEO's/chairman's reputation more if the company should fail (Semadeni, Cannella, Fraser, & Lee, 2008), thus increasing the incentive of the CEO to avoid business failure. Individuals who have high levels of identification with their organization are more likely to choose stewardship because they feel a strong sense of membership with their organization (Lee & O'Neill, 2003; Vallejo, 2009; Zahra et al. 2008).

2.3 Empirical Evidence of Business Failure

Over the last four decade, the incidence of bankruptcy cases has led to a growing interest in business failure prediction from researchers and has developed into a key research area in finance. Previous studies evolve around the search for the best business failure prediction model for both listed corporations and small businesses using different statistical techniques such as univariate analysis, multiple discriminant analysis (MDA), logistic regression, probit model, hazard model and artificial neural network (ANN). Altman's (1968) work is the pioneering studies of bankruptcy prediction model using financial ratios among the US listed companies by using multivariate discriminant analysis. Since Altman (1968) model, a number of bankruptcy prediction models have been developed in the literature. However, majority of researchers have been putting a lot more effort into building business

failure prediction models in developed countries with little evidence from developing countries.

This section reviews literature of business failure among SMEs. It is divided into three sections. The first section highlights the evolution of business failure prediction studies. The second section concentrates on studies of business failure of SMEs in developed countries while the third section reviews the studies of business failure of SMEs in developing countries.

2.3.1 Evolution of Business Failure Prediction Studies

The study of Fitzpatrick (1932) is considered the first study that investigate between bankrupt and non-bankrupt firms' financial ratios. The study did not perform statistical analysis, but thoughtfully interpreted the ratios and trends in the ratios. He compared financial ratios of 20 companies, one failed and one surviving, matched by date, size and industry. He finds in majority of the studied firm, the successful companies displayed favourable ratios while the failed firms had unfavourable ratios when compared with standard ratios and ratio trends. He concludes that liquidity ratio, debt ratio and turnover ratios form a significant differences between bankrupt and healthy firms. Similarly, Beaver (1966) compared the mean values of 30 ratios of 79 failed and 79 non-failed firms in 38 industries. Using univariate discriminant analysis, he find net income to total debt had the highest predictive ability (92% accuracy one year prior to failure), followed by net income to sales (91%) and net income to net worth, cash flow to total debt, and cash flow to total assets (each with 90% accuracy).

In 1968, the first formal multiple variable analysis was introduced by Altman (1968). He applied multiple discriminant analysis (MDA) within a pair-matched sample to develop a five-factor model to predict bankruptcy of manufacturing firms. One of the most prominent early models of bankruptcy prediction is the Z-Score. The Altman Z-Score model is based on five financial ratios and has an accuracy of 95 percent for the initial sample one year before failure. Though, the model's predictive ability dropped off significantly from there with only 72 percent accuracy two years before failure, down to 48, 29, and 36 percent accuracy three, four, and five years before failure, respectively. The model's predictive ability when tested on a hold-out sample was 79 percent. Since Altman (1968), many researchers have used the MDA, making some alterations, incorporating or replacing new ratios which were significant on different samples and business environment (Barnes, 1987; Blum, 1974; Deakin, 1972; Taffler & Tisshaw, 1977).

However, authors have subsequently pointed out some violations in basic assumptions of the MDA when the model is applied to predict business failure. The independent variables have to be multivariate normal (Ohlson, 1980). However, in practice, the assumption of multivariate normality is often violated. The normal distribution of the variables does not allow the use of dummy variables. Furthermore, the variance and covariance matrix must be the same in the case of bankrupt and non-bankrupt firms (Deakin, 1976; Taffler & Tisshaw, 1977; Balcean & Ooghe, 2004; Barnes, 1987). Additionally, MDA does not predict the probability of failure, it classifies firms into groups (bankrupt or non-bankrupt) based on each firm's characteristics (ratios/factors). Therefore, other alternative methods were introduced such as probit analysis and logistic regression analysis. Logistic

regression analysis and probit analysis take into account the probability that the firm will go bankrupt. Ohlson (1980) applies logistic regression analysis (logit model) to predict business failure of 105 bankrupt firms and randomly chosen 2,058 non-bankrupt firms over the 1970 to 1976 sample period, using only the financial ratios. Ohlson's logit model classification accuracy achieves 96.3 percent. Since the work of Ohlson (1980), subsequent studies have shown that logit model is empirically superior to MDA in both classification and predictive accuracy and is more often used and preferred. This is because logistic regression analysis does not need the normal distribution of the variables and the covariance matrix does not need to be equal.

Logit models are however, consider as single-period bankruptcy models and they give biased and inconsistent probability estimates because bankruptcy occurs infrequently and firm's characteristics change from year to year (Shumway, 2001). Hazard models use time varying variables to estimate a firm's bankruptcy risk at each point in time and was first introduced by Shumway (2001). He compared hazard model to the MDA and logit and finds that majority of previously used accounting variables from Altman (1968) and Zmijewski (1984) have little power in forecasting bankruptcy. He further finds that a combination of accounting and market-driven variables such as past stock returns and idiosyncratic risk increases forecasting accuracy significantly. He further finds that hazard model forecasted bankruptcy better compared to logit and MDA models. However, hazard model is believe to focus more on determining the effects of explanatory variables on the life of businesses, rather than being designed to predict outcomes such as the failure of businesses (Gepp & Kumar, 2012).

Information technology has brought new approaches in bankruptcy prediction through artificial intelligence and managerial systems such as recursively partitioned decision trees, case-based reasoning models, genetic algorithms, and rough sets mode (Aziz & Dar, 2006). However, the use of artificial neural network (ANN) in bankruptcy prediction model appears in the late 1980s and, in the 1990s. It has becomes one of the primary method used in many studies. ANN is a designed to emulate the human pattern recognition function. Studies show that ANN is a powerful tool for pattern recognition and pattern classification due to their nonlinear, nonparametric adaptive-learning properties (Coates & Fant, 1993; Murtaza & Shah, 2000; Zhang et al., 1999). The first attempt to use ANN to predict bankruptcy is made by Odom and Sharda (1990). In their study, three-layer feed-forward network is use and the results are compared to those of MDA model. Using different ratios of bankrupt firms to non-bankrupt firms in training samples, they test the effect of different mixture level on the predictive capability of neural networks and discriminant analysis. The finding show that the neural network appears to be more robust, performing better than the discriminant analysis method in different levels. Neural network also appears to be more consistent than the discriminant analysis method.

2.3.2 Empirical Evidence from Developed Countries

The increasing business failure among small businesses in the US motivated Edmister (1972) to adopt Altman (1968), Beaver (1967) and Blum (1968) bankruptcy prediction models of listed companies based on financial ratios to seek evidence among small businesses in the same market. Their studies suggests that analysis of selected financial ratios are useful to predict failure of listed firms. Using

19 selected financial ratios from their studies, Edmister (1972) employs the multiple discriminant analysis (MDA) statistical technique to discriminate among failed and non-failed SMEs. He find that for one year prior to failure, seven financial ratios are found to be significant in predicting business failure among small businesses, which include annual fund flow to current liabilities, equity to sales ratio, working capital to sales ratio, current liabilities to equity, inventory to sales ratio, quick ratio to Robert Morris Associates (RMA)⁶ up-trend. The finding further implies that financial ratios are applicable to predict business failure of small firms.

Following Edmister (1972), the research field extends on developing prediction models using qualitative data as researchers claimed it also provide a comprehensive or unified explanation for small firm failure. Lussier (1995) utilises qualitative data to predict business failure among US SMEs which was consider among the first model that utilised such data. The model consists of fifteen major variables identified in twenty studies. The model is non-financial and it uses resource-based theory (RBT) as it helps to better understand the role of resources in new ventures by focusing on the identification and acquisition of resources that are crucial for the firms' long-term success (Lichtenstein & Brush, 2001). The finding show that successful firms had fewer difficulties in finding and retaining qualified personnel than the failed firms. Contrary to expectations, the finding show that owners of failed firms had more industry, work, management and life experience (AGE).

⁶ The relative level of the borrower's ratio to the average ratio of other small businesses in the same industry is hypothesized to be a predictor of small business failure. Support for including an industry adjustment is widespread and the popularity of industry comparison is indicated by the prolific construction and publication of industry summaries by Robert Morris Associates (RMA). To test this hypothesis, variables denoted as RMA relatives are calculated by dividing the original ratio by Robert Morris Associates' annual statement studies average ratio for firm in a similar industry and of similar size.

Gimeno-Gascon and Woo (1991), Flerackers (1998), and Reynolds and Miller (1989) find similar results regarding these variables. A possible explanation for these results is that there is needs for a young, fresh and flexible mentality in order to be a successful entrepreneur, and not a mentality that has been fixed too much by all the years of experience.

Moreover, the studies reveals that failed firms prepared more detailed financial, personnel and overall plans than successful firms (Gimeno-Gascon & Woo, 1991; Flerackers, 1998; Reynolds & Miller, 1989). This can be explained by the fact that “out-of-the-box-thinking” is required in order to successfully run a business. Houben (2000) and Braunschweig (2003) also mention the risk of exaggerating planning. Contrary to expectations, it appears that having a business partner does not increase the chances of success. This can be explained because one cannot have two captains on a ship; this will ultimately go wrong and cause problems. Cooper et al. (1991) also finds that having a partner is not a predictor for survival. The model correctly predicts 81 percent of the successes and failures in the sample, which is consistent with the Lussier (1995) model. Consistent with the studies of Lussier and Pfeifer (2001) and Teng et al. (2011) find that staffing is a significant predictor among the non-financial factors while Lussier and Pfeifer (2001) find education to be a significant factor among the non-financial factors. Furthermore, managerial expertise is also found to be significant in explaining distress among SMEs. Lussier’s (1995) model is tested and replicated by other researchers outside the US market such as by Houben, Bakker and Vergauwen (2005). However, this study would not apply these significant variables as they are qualitative in nature. The variables intended to be used are secondary data (financial and non-financial,

governance information), using information from SMEs' financial statement and other corporate information.

However, Altman and Sabato (2007) stress on the importance of financial variables in explaining financial distress among the SMEs and extended the work of Edmister (1972) by using the definition of new Basel Capital Accord (sales less than EUR50 million). Data were derive from COMPUSTAT which consist of 120 failed SMEs and 1890 non-failed SMEs for the period between 1994 to 2002 by using logistic regression and MDA. The model of Altman and Sabato (2007) shows that short-term to equity book value, EBITDA to total assets, EBITDA to interest expenses, cash to total assets and retained earnings to total assets are significant predictor of SMEs default in the US. Furthermore, the empirical result shows that the prediction accuracy could be enhanced by 30 percent if a prediction model specific to SMEs was used on the holdout sample. The logit model used in their analysis performed slightly better in discriminating between failed and non-failed companies than the MDA. The finding contradicted with the work of Bellovary (2007) which show that MDA had more predictive accuracy than that of logit model in his review of failure prediction studies.

Changes in the UK 1981 Companies Act which allow small companies to submit only an abridged⁷ set of accounts to Companies House. Keasey and Watson (1987) believe that in the absence of reliable and timely financial information from which to construct ratios, other sources of information will be needed in order to assess the

⁷ The abridged accounts consist of only a highly aggregated balance sheet and accompanying notes which may be of limited analytical value.

probability of small company failure. Using Argenti's (1976) model⁸, Keasey and Watson (1987) utilize logistic regression analysis to predict small business failure in the UK. The study used sample of 73 failed companies and 73 non-failed companies from 1970 to 1983. The finding show that model 1 (financial ratios only) has an accuracy rate of 76.7 percent, model 2 (non-financial only) has 75.3 percent accuracy rate and model 3 (financial and non-financial) has the highest accuracy rate of 82.2 percent. Similarly, the holdout sample show that model 3 provides a better overall prediction rate. The results show that slightly better predictions regarding small company failure may be gained from non-financial data compared to using only financial ratios.

Cressy (1992) later improve on the work of Edmister (1972) in the US and Keasey and Watson (1987) in the UK by showing that a five-year lag structure in financial ratios generates the best model for the data. He also examines the influence of industry effects on small firm bankruptcy potential. Using logistic regression and a set of 636 small UK firms from 27 different industries, the results demonstrate that several years' data on financial ratio variables are required to provide reasonable predictive accuracy on small firm solvency rather than the one year accounts information traditionally used by Edmister (1972) and Keasey and Watson (1987). Cressy (1992) find that among the variables used, only profitability (net profits/total assets) is statistically significant and appear in all models (financial, financial plus industry and financial plus year regression) and in all prior year samples. Similarly, net profit relative to total debt also consistently appear to reduce the probability of

⁸ Argenti's (1976) model is on the believe that financial ratios are not sufficient in predicting business failure because failing companies would attempt to manipulate their financial statements in order to hide the sorry state of the company from outsiders such as creditors and customers.

bankruptcy in the early years. The results suggests that profitability measures should be regarded as the major determinant of bankruptcy for small firms. However, the finding show little evidence that industry effect has significant influence on business failure prediction of small business in the UK. Cressy (1992) recommend that since the industry effect may reflect unrepeatable historical trend in industry, he recommends the financial trend model over the financial plus industry model for policy purposes.

Furthermore, Altman, Sabato and Wilson (2010) explore the effect of the introduction of non-financial information as predictor variables into the models developed by Altman and Sabato (2007) in the US. They employed a large sample from the UK which includes 5,749,188 sets of accounts for businesses that survive in the period 2000 to 2007 and 66,833 companies that fail during those periods. The data analyse for failed companies are the last set of accounts filed in the year preceding insolvency. Their finding show that qualitative data relating to such variables as company filing histories, legal action by creditors to recover unpaid debts, comprehensive audit report/opinion data and firm specific characteristics make a significant contribution to increase the default prediction power of risk models built specifically for SMEs. The finding is consistent with the study of Blanco, Irimia and Oliver (2007) who also examine the effect of non-financial information of 38,570 small firms (50 percent non-default companies and 50 percent default companies) in the UK.

Using more recent data, Khorasgani (2011) further sheds lights on the concepts of industry and corporate governance effect on the UK SMEs default prediction. He

employs more than 30,000 UK SMEs covering the period from 2000 to 2008. The study uses two widely applied probabilistic models for firm's default which are Altman's (1968) MDA and Ohlson's (1980) logit regressions. Three explanatory variables, pre-tax income plus depreciation and amortization divided by total liabilities (FFOTL), current liabilities divided by current assets (CLCA) and net income divided by total assets (NITA) were not significantly affecting the probability of default (PD) while dummy for owner's equity (OENEG) and the scaled change in net income (CHIN) have shown an opposite relationship with probability of default for the UK SMEs Ohlson's model. For Altman's model, the results of the regression indicate that all variables except leverage is positively affecting the SMEs default prediction which is compatible with the relevant literature. Additionally, leverage and profitability ratios are highly significant at the one percent level while activity ratio is barely significant at the 10 percent level whereas liquidity is not significant. All the time dummy variables use in the model are highly significant which indicates the important effect of time factor on default prediction models. The results of the regression including the industry effect and structural effect indicate that the UK SMEs default events are highly affected by the different industry traits and also firms' governance structure. For instance, in the case of Altman's model by including the industry and structural effect in the model increased the reliability and validity of the model substantially. Moreover, the results for both Altman's and Ohlson's model suggested that the UK SMEs private sectors are more risky than the public sector. The average accuracy rate of the Altman's model is 83.5 percent while Ohlson's model accuracy rate is 72 percent. The superiority and efficiency of the Altman's model is also supported by the lower type I and type II errors (Altman's model type I error rate is 12% and type II error

rate is 21% while Ohlson's model type I error rate is 20% and type II error rate of 36%).

Luppi, Marzo, and Scorcu (2007) were among the early bankruptcy prediction studies of SMEs in the Italian market. The study used a multiple-factor credit risk model to provide new estimates of default probabilities in a sample of 3,900 Italian SMEs in the retail industry. The finding show that debt ratio is positively related to failure. Firms with greater cash flows, EBITDA and return on investment (ROI) are less likely to fail. The variables serve as an important factor in estimating failure among SMEs in Italy. However, the finding show that ROE is insignificant in explaining SMEs failure. Luppi et al. (2007) suggests that this is due to the small portion of equity to finance SMEs as funds largely come from debt financing provided by banks. The finding are consistent with later studies in Italy such as Ciampi, Vallini and Gordini (2009) and Pederzoli and Torricelli (2010) whom also found that profitability, liquidity and leverage ratios can correctly predict default. The prediction accuracy rate of the model is 85 percent. However, Ciampi et al. (2009) argued that the work of Luppi et al. (2007) failed to use the best documented statistical method, MDA and logistic regression. Therefore, they used MDA, logistic regression and Artificial Neural Network (ANN) to a sample of over 6,000 small Italian firms. The overall prediction accuracy of ANN is 68.4 percent higher than logistic regression with 67.2 percent and MDA with 65.9 percent. The finding show that ANN prediction is more accurate.

The first study in Italy that analyse the relationship between corporate governance mechanisms and business failure in SMEs by using logistic regression with a total

sample of 934 Italian SMEs was done by Ciampi (2015). The finding show that model 2 which combined economic–financial variables with corporate governance variables improves SME default prediction accuracy rates to 87 percent, compared to model 1 which only used economic–financial variables that shows an accuracy rate 74.7 percent. CEO-duality is negatively significant in predicting default among SMEs in Italy. It shows that in the case of SMEs, presence of CEO duality reduces the likelihood of business failure. Therefore, if such power is reduced by the presence of a chairman of the board other than the CEO, the risk of the company failing grows. This is in contrast to the literature on larger companies. The presence of outside directors is having a negative correlation with SMEs default, thus confirming that a board with a sufficient number of outsiders can help small firms to form “a system of checks and balances designed to improve executive monitoring and benefit the firm's owner”.

However in contrast, Dalton et al. (1999), Keasey and Watson (1987) and Abdullah et al. (2016) finds that large boards are associated with better performance, and that this phenomenon is particularly strong for small businesses. The studies show that board size does not have a significant impact on the likelihood of small company default as the coefficient is not significant. Furthermore, the finding show that ownership concentration is significant and negatively correlated with SMEs default.

A joint consideration of classic financial ratios and relevant external indicators leads Monelos, Piñeiro and Rodríguez (2011) to build a basic prediction model focus on non-financial Galician SMEs whom contribute 5.4 percent to Spain GDP. The study used discriminant analysis and logistic regression. The total sample consists of 384

SMEs that have filed for bankruptcy within the last ten years and 107 healthy SMEs which have not filed for bankruptcy, nor are listed in insolvency public registers within the last ten years between 1999 and 2009. The results show that in addition to financial predictors of business failure among SMEs, enhancement of the reliability of models could be achieved by including additional variables regarding external auditing: average duration of auditors' contracts, rotation, rate of qualified opinion report, and non-observance of duties regarding the publication of financial information. All variables are found to have predictive ability of business failure among SMEs. The finding show that SMEs suffering financial distress have a peculiar auditing profile: high rotation of auditors, short term contracts, cost interdependencies (complementary services), an abnormally high rate of disclaimer of opinion report, difficulties to meet external information duties (file and disclosure of financial statements), and even audit omissions. These variables will not be used in this study as the information is not available for both Malaysia and Nigeria.

Furthermore the predictive accuracy of the methods used in prediction shows that MDA has an accuracy rate of 80 percent while logit model has an accuracy rate of 97 percent. MDA models reach good results in identifying distressed companies, and a relatively poor performance in healthy companies, while logit models seem to be more suitable to identify healthy companies; therefore, MDA models tend to overstate bankruptcy probability, while logit models seem to systematically undervalue the inherent credit risk of the company. As such Monelos et al. (2011) suggested that, even though they both offer high explanatory and predictive abilities, logit and MDA models should be used and interpreted jointly.

Spanish SMEs and their lenders avoid filing for bankruptcy by making possible that creditors foreclose on the company's assets. Most of the SMEs secured credits are mortgage loans (i.e., loans secured on land and buildings), debt enforcement takes place via mortgage foreclosures. García-Posada and Mora-Sanguinetti (2013) investigate how the mortgage foreclosure reduce the probability of default among SMEs in Spain compared to their counterparts in France and the UK. The study uses data on SMEs from three countries: Spain, France and the UK for only one year period i.e. financial data for 2008. The overall sample consist of 150,000 observations comprising both SMEs under bankruptcy proceedings (bankrupt firms) and businesses that have not filed for bankruptcy (non-bankrupt firms). The study uses age, firm size and dummies for industry as controls. The finding reveal that tangibility (the assets that can be used as mortgage collateral) is negatively correlated with the probability of bankruptcy in Spain and a higher proportion of tangible fixed assets over total financial debt significantly decrease the probability of bankruptcy among Spanish SMEs, while tangibility is positively correlated in France and the UK. With respect to the control variables, the finding show that size has a negative impact in the probability of bankruptcy, suggesting as older firms have more lenders, higher coordination costs reduce the chances of bankruptcy.

Majority of the bankruptcy prediction literature in France revolve around comparative analysis between the bankruptcy prediction methods in order to develop models with the highest predictive accuracy to be used by financial institutions and regulators. For example, Marouani and Bellier (2014) study compared the predictive power between a logistic regression and a standard Cox proportional hazard model. The study find that variables related to payment

behaviour seem to be good indicators. For example, the impact on SMEs' probability of default is higher for firms with unpaid trade bills, default in payment to State creditors, commercial litigations or a negative rating and the incident of payment. However, in terms of classification accuracy rate of the models used, the study found that logistic regression and standard Cox PH provide similar results. The models accuracy rate using the logistic regression model is 69.5 percent while the standard Cox PH classification rate is 70 percent. Both approaches are similar in term of their performance tests.

Rommer (2005) is the first study that compare the determinant of business failure among small businesses in three European countries namely France, Italy and Spain. The study investigate whether the predictors of business failure in the countries are the same or not. To compare the determinants of financial distress, accounting-based credit-scoring models for each country were estimated. The study use a large sample of 282,131 SMEs across the three countries (France: 108,533, Italy: 97,732, Spain: 75,866) covering the years between 2000 and 2002. The study categorised the variables into three groups namely; core, proxies and control variables. The result from the analysis of the credit-scoring models show that there are some similarities across countries. The core variables that are significant across the countries are the profitability/earnings ratio and the solvency ratio which are significant and have a negative sign. The proxy variables that are significant across the countries are the number of subsidiaries, the number of shareholders and the ownership variables.

However, loans to total assets ratio, size, age and legal form effects differ between the countries in terms of their significant and sign. When a model including all

countries is estimated, the results show that the model delivers parameter estimates that differ to quite an extent from each country's credit-scoring models. The parameter estimate is significant and has a positive sign in the French and the Spanish case. The variable is insignificant in the Italian credit-scoring model. A reason for this could be that in comparison with French and Spanish firms, Italian firms fund themselves to a greater extent through trade creditors. The comparison of the core variables in the model including all countries with the individual country models, the result shows that the country that resembles the model including all countries the most is France. Therefore the model including all countries does better for France than the French credit-scoring model, but worse for Spain and Italy than the Spanish and the Italian credit-scoring models.

Furthermore, Ferreira, Grammatikos and Michala (2014) extended the study of Rommer (2005) in terms of sample, variables, statistical method and number of countries. Ferreira et al. (2014) explore the performance of distress prediction hazard models for non-financial SMEs using a dataset from eight European countries (Czech Republic, France, Germany, Italy, Poland, Portugal, Spain and the United Kingdom) over the ten-year period between 2000 and 2009. The study sample consists of 2,721,861 firm-years observations (644,234 firms) out of which 49,355 are distressed. Model I considers only financial variables and all firm-specific variables are significant and have the expected signs, specifically, the probability of distress is negatively related to profitability (earnings before taxes to total assets), coverage (EBITDA to interest expenses), cash flow (cash flow to current liabilities), activity (turnover to total liabilities) and positively related to leverage (current liabilities to total assets). Model II combines financial and

systematic variables. All the financial variables maintained their significance as in model I and in addition five systematic variables, namely the foreign exchange rate change, unemployment, economic sentiment indicator, and the change in bank lending are significant in predicting distress among SMEs in the eight European countries.

To check the robustness of the models develop, Hosmer and Lemeshow and Receiver Operating Characteristic (ROC) curve were employed. According to the Hosmer and Lemeshow grouping, the percentage of distressed firms in the last three deciles increases from model I to model II (75.83 percent to 76.59 percent respectively) while area under the curve (AUC) also increases from 0.8241 in model I to 0.8382 in model II. The result was better than those achieved by previous studies particularly in Altman et al. (2010), where the AUC figure ranges between 0.78 and 0.80.

Hu and Sathye (2015) utilises macroeconomic variables in failure prediction model of SMEs in Hong Kong. The study utilised 150 SMEs that are listed in the Hong Kong Growth Enterprise Market (GEM). The sample consist of 45 distressed SMEs and 105 non-distressed SMEs for the period between 2000 and 2010. The study find that gross profit rate, the frequency of firm changing its auditors, the frequency of auditors' report with qualified/explanatory paragraph and business climate index are all found to be significantly related to financial distressed of SMEs. The study also find that a model that includes firm-specific financial variables, firm-specific non-financial variables and a macroeconomic variable is a better predictor of business

failure than a model that includes only the first set of variables or a model that includes the latter two sets of variables.

2.3.2 Empirical Evidence from the Developing Countries

Studies on bankruptcy prediction models started late in developing countries compared to developed countries. Majority of the bankruptcy studies in developing countries evolve around listed companies due to the easy access of their published information. However, studies based on SME are very rare in emerging markets. The importance of bankruptcy prediction for SMEs in developing countries was driven by economic development and the needs for businesses, financial institutions and regulatory bodies to have a robust model that could detect bankruptcy among companies. Financial institutions in developing market faced with a lot of uncertainty about the risks involved in lending to SMEs. Therefore developing a bankruptcy prediction model is of significant important towards economic development and sustainability.

Similarly in Malaysia, majority of the bankruptcy prediction literature are on listed companies. Abdullah et al. (2014) is the first study that examined 132 privately-owned SMEs in the manufacturing sector during the period between 2000 and 2010. Their empirical results show that higher gearing and lower profitability entailed higher probability of failure and when firm age (non-financial variable) is added to the model as non-financial variable, they found it to be significant and increase the model's classification accuracy rate. Receiver operating characteristics (ROC) curve demonstrates that both models possess better predictive ability than a random model, but model two which includes financial and non-financial variables show

superior performance. The accuracy rate that the model could correctly predict failures ranges from 75 to 89 percent and the model could be used as a refined tool to avoid possible adverse situations among the SMEs. The finding of Abdullah et al. (2014) is consistent with Abdullah et al. (2016), where they get an almost similar accuracy rate. The finding is also consistent with the study of Lugovskaja (2009) in Russia where the model with financial and non-financial variables had a higher classification accuracy rate of 77.9 percent for the estimation sample and 79 percent for the holdout sample; whereas a study by Behr and Guttler (2007) from the German market with an accuracy of 85 percent using financial and non- financial variables.

Furthermore, Abdullah et al. (2016) extended the study of Abdullah et al. (2014) in terms of predictors, sample size and period of investigation. The study investigate on the value added of corporate governance variables to failure prediction of SMEs in the manufacturing sector. The study period and sample were all expanded to 172 privately-owned SMEs for a period between 2000 and 2012. Results show that higher gearing and lower profitability entailed higher probability of failure. The finding appear to be consistent with that of Abdullah et al. (2014) where they find that debt ratio is significant to predict financially distressed SMEs at all prior periods of the study. Altman (1968), Beaver (1970), Blanco et al. (2007), and Shane (1996) also reported that debt ratio had a significant predictive ability. Moreover, among the governance variables, controlling shareholders has a positive and significant relationship with SMEs failure, indicating that the greater the holding of controlling shareholders, the higher is the likelihood of failure among SMEs.

In addition, number of directors in SMEs board is found to be having a negative relationship with SMEs failure. This indicates that a larger board can decrease the probability of SMEs failure due to increase oversight and expertise. The finding is consistent with that of Keasey and Watson (1987). More so, gender of managing director is also found to be significant and positively related to corporate failure. The results show that men managing director are more likely associated to failure among SMEs than the female counterpart. In recent years, the number of female-led firms are growing globally which signal the importance of female leadership of firms (Singhathep & Pholphirul, 2015). The performance of firms led by female has been usually studied across various countries, such as, Australia (Robb & Watson, 2010; Watson, 2002), Laos (Inmyxai & Takahashi, 2010), Malawi (Chirwa, 2008), Malaysia (Amran, 2011), Taiwan (Hsu, Kuo, & Chang, 2013), and the USA (Fairlie & Robb, 2009; Fasci & Valdez, 1998; Cuba, DeCenzo, & Anish, 1983; Robb & Watson, 2010). However, most of these studies have shown mixed results.

For Thailand, Sirirattanaphonkun and Pattarathammas (2012) is the first to develop default prediction model (or credit risk model) for Thai SMEs. The study used bank data in order to predict failure as banks required SMEs to submit their financial data as part of a loan agreement. Data were also derived from private and public authority of Thailand such as the business online public company limited database. The sample cover the period 2000 to 2010 with 353 SMEs. Variables such as liquidity ratio, profitability ratio and leverage ratios appear to be statistically significant. The finding is consistent with the study of Chotima (2013), who uses same financial ratios used by Sirirattanaphonkun and Pattarathammas (2012) to investigate bankruptcy prediction among manufacturing SMEs in Thailand. The

results show that the logit model gives a higher predictive accuracy rate at 85.5 percent for out-of-sample test compared with MDA with 80.5 percent accuracy rate. Furthermore, the estimated sample of bankruptcy firms from both MDA and logit models could help achieve a higher predictive accuracy level. However, Chotima (2013) logit model achieved a higher prediction accuracy rate of 87.9 percent.

The first study of SMEs failure prediction in Croatia was motivated as a result of high business failure rate when the country's economy experienced recession in 2009. Sarlija and Jeger (2011) developed 3 models (Model 1: 2006/2007; Model 2: 2007/2008 and Model 3: 2008/2009) to compare business failure prediction models develop for three consecutive years that capture time of prosperity. The objective was to see the effect of change in macroeconomic condition as well as market dynamic to financial ratio in the business failure prediction model. The models are based on financial data from 2000 privately-owned SMEs in Croatia. The study finds that ROE, long term asset to equity plus long term liabilities and equity to sales ratio as a source of funding are significant in model 3. Leverage ratios were significant in model 2 but insignificant in model 3. This finding imply that the lack of funding sources did not have a significant negative impact on companies that successfully redesigned their business activities and maintained good relationships with customers and suppliers. The study also found that five ratios are consistently appeared in predicting business failure in all the three models which include ROE, operating revenue to operating expenses ratio, long term asset to equity plus long term liabilities ratio, short term liabilities to total asset ratio and equity to sales ratio. Model 1 scores the highest predictive accuracy rate of 84.3 percent, then followed

by model 2 with a predictive accuracy rate of 81.1 percent and the least among the models developed is model 3 with a predictive accuracy rate of 79.2 percent.

Accordingly, Pervan and Kuvek (2013) later improve on the finding of Sarlija and Jeger (2011) by exploring the relative importance of non-financial variables in predicting of insolvency among SMEs in Croatia. The observation period was 2010 as the study aimed at predicting default one year prior by using a logit model on a sample of 825 SMEs of which 127 firms were defaulted, while 698 firms were non-defaulted. The non-financial variables used in the study include; firm age, size measured by number of employees, quality of accounting information, dependence on key customers, firm owners' personal credit performance and management quality. The finding show that among the financial variables, debt to assets, equity to fixed assets, operating cash flow to assets and net income to assets were found to be significant predictors of default among SMEs. While quality of accounting information, firm owners personal credit performance and management quality were among the significant predictors of default among nonfinancial variables.

Furthermore, classification results indicate that combined model has outperform financial variables model. The combine model is having a classification accuracy rate of 88.4 percent while financial variables model had a classification accuracy rate of 52.0 percent (Sarlija & Jeger, 2011). The obtain results confirmed that a model with financial and non-financial variables outperform a model with financial variables in default prediction which are in line with previous similar research (Abdullah et al., 2014; Abdullah et al., 2016; Altman et al. 2008; Moscalu, 2012; Sarlija & Jeger, 2011).

Among the SME failure prediction studies, Aneta and Anna's study (2014) is among the first to predict failure among Polish SMEs combining financial ratios in Altman's Z-Score and macroeconomic variables. The objective of their study is to explore the impact of macroeconomic variables on failure prediction of SMEs. The total sample of SMEs in the study consists of 1547 healthy enterprises and 494 default enterprises covering a time range from 2002 to 2012. In the Cox regression model with original Altman's variables (ratios), all the five ratios estimated were significant. The strongest influence was like in Altman's Z-Score for ratio X3 (earnings before interest and taxes to total assets). The model with macroeconomic variables show that the higher the GDP and unemployment rate levels the lower the risk of enterprises' default. However, inflation rate is not significant. The model that incorporate financial and macroeconomic variables was having the highest predictive accuracy power of AUC 0.827 compared with AUC 0.746 for the model that is mainly financial. The result indicates that macroeconomic variables increase the effectiveness of the model. In view of financial downturn and other economic activities that affect the general economy, it is essential to take account of macroeconomic variables since the economy has a huge impact on the ability of customers to settle liabilities.

2.4 Determinant of SMEs Failure Prediction Studies

According to evolution of the bankruptcy prediction studies both in developed and developing countries, the categories of variables used in previous studies include financial ratios (profitability, liquidity, leverage, activity and solvency), non-financial, corporate governance and macroeconomic variables. This section discusses these determinants of bankruptcy.

2.4.1 Financial Indicators

Financial indicators are internal or external factors that influence the performance of a firm. Management effectiveness (or ineffectiveness) and good (or poor) strategic implementation of the financial indicators can usually lead to the success (or failure) of a firm. Review of literature show that there are four major categories of financial indicators which are found to be significant predictors of SMEs' failure, which include: profitability, leverage, liquidity and asset management. Following the pioneering study of Edmister (1972) on SMEs business failure, studies have been carried out in search for the best set of explanatory variables that could correctly predict failure of SMEs using different set of financial ratios and modelling techniques (refer to section 2.3, Altman & Sabato, 2007; Arslan & Karan, 2009; Chotima, 2013; Fidrmuc, Hainz & Malesich, 2006; Jabeur & Fahmi, 2014; Khorasgani, 2011; Moscalu, 2012; Rommer, 2005; Sarlija & Jeger, 2011; Sirirattanaphonkun & Pattarathammas, 2012; Storey et al., 1987; Teti, Dell'Acqua & Brambilla, 2012).

Profitability is the primary goal of all businesses because without profit, a business will not survive and sustain in the long run thereby going into distress. Pecking order theory also maintains that businesses with high level of profitability adhere to a hierarchy of financing sources and prefer internal financing when available, and debt is preferred over equity if external financing is required (Myers, 1984). The commonly used proxies for profitability are net profit to total assets (Abdullah et al., 2014; Lugovskaja, 2009; Storey, Keasey, Watson & Wynarczyck, 1987) and pre-tax profit to total assets (Ferreira, Grammatikos & Michala, 2014; Moscalu, 2012). Profitability measures should be regarded as one of the major determinant of

business failure for small firms and one for which the influence of trends is paramount. The less profitable an SME is, the more likely it is to face financial distress and creditors will look to a liquidation to recover some of their funds.

Financial risk of a firm is often measured by leverage. High leverage is good for a company as proposed by MM proposition II, where a firm would enjoy the advantage of interest tax shield (Modigliani & Miller, 1963). However, at a certain point when the leverage increases, the financial and bankruptcy risk of the business will also increase as suggested by the trade-off theory (Robichek & Myers, 1965). Studies use different measurement for leverage and majority of the studies find leverage to be a significant predictor of business failure among SMEs. The study of Edmister (1972) who uses current liabilities to equity to measure leverage, find that leverage is positive and a significant predictor of business failure. High level of gearing will potentially lead to business failure of the firm and a low debt-to-equity ratio relative to the industry reduces the chance of failure. Total debt to total assets (Behr & Guttler 2007; Kornell & Wallin 2011; Luppi, Marzo, & Scorcu, 2007; Monelos et al., 2012; Pederzoli & Torricelli 2010; Pervan & Kuvek, 2013), current liabilities to total asset (Abdullah et al., 2014; Chotima, 2013; Ferreira, Grammatikos & Michala, 2014) and short-term debt to equity (Altman & Sabato, 2007; Rommer, 2005) are the commonly used proxies for leverage and are positively related to SMEs failure.

Liquidity measures are a class of financial ratios that are used to determine a company's ability to pay off its short-term and long-term debt obligations when due. Generally, the higher the value of the ratio, the larger the margin of safety that

the company possesses to cover fixed obligations which will reduce the probability of default. SMEs rely heavily on short and long term borrowing as their major source of financing as such liquidity factors are consider important determinants of SMEs failure due to the nature of SMEs business operations. The mostly used proxies for liquidity are the current assets to current liabilities (Abdullah et al., 2014; Cressy, 1992; Fidrmuc, Hainz & Malesich, 2006; Khorasgani, 2011; Storey et al., 1987), EBIT to interest expenses (Ferreira et al., 2014; Fidrmuc et al., 2006; Teti et al., 2012), cash to total assets and current asset minus inventory to current liabilities (Moscalu, 2012). Empirical analysis show that all these measures for liquidity are negative and significant predictor of SMEs failure. High liquidity lower the default probabilities of the SMEs significantly while a lower funds flow relative to short-term commitments is a predictor of failure.

Activity based ratios which are sometimes refers to asset management or efficiency ratios is another category of financial indicators that are commonly used in business failure prediction. Activity ratios measure a firm's ability to convert different accounts within its balance sheets into cash or sales. They are used to measure the relative efficiency of a firm based on the use of its assets, leverage or other balance sheet items. Working capital to sales ratio as measure for activity ratios is negative and significant predictor of small businesses failure, indicating that a relatively high working capital turnover signals failure (Edmister, 1972). Similarly, sales to total assets is also used as a proxy for activity ratio (Abdullah et al., 2014; Pederzoli & Torricelli, 2010). The variable is negative and significant predictor of business failure in Italian context indicating a high value for the sales to total asset indicator means good performances on the market and, therefore, a low probability of default

(Pederzoli & Torricelli, 2010). However, the variable was not significant predictor in the Malaysian manufacturing SMEs (Abdullah et al. 2014).

2.4.2 Non-Financial Indicators

Non-financial indicators rests on the basis that the use of financial measures as sole indicators of organisational performance is not enough (Behr & Guttler, 2007). Financial ratios use in business failure prediction studies have received a lot of debate within the corporate finance literature as they are determined based on past performance, and thus the prediction models may not be suitable for future failure prediction (Foster, 1986; Keasey & Watson, 1987). The use of historical cost in accounting principles may affect the significance of the prediction models since there is a tendency of manipulations of information especially in the case of SMEs where there is lack of sound and effective internal control mechanism (Agarwal & Taffler, 2007).

Business failure prediction models that compliments financial and non-financial variables are found to overcome some of the drawbacks associated with financial ratios mentioned earlier by providing a higher predictive accuracy rate and increase the validity of the models developed. A growing number of studies have confirmed that financial indicators together with non-financial indicators (such as business age, education of managers, auditing, business location, firm's industry) may prove useful in business failure prediction for SMEs (refer to section 2.3, Abdullah et al., 2014; Abdullah et al., 2016; Altman et al. 2010; Blanco et al., 2010; Cressy, 1992; Ferreira, Grammatikos & Michala, 2014; Hu & Sathye, 2015; Keasey & Watson, 1987; Lussier 1995).

SMEs size and age are among the non-financial variables that have been given much attention by researchers due to the nature and structure of small businesses. Age and firm size (normally represented by total assets or share capital) are found to be negative and significant predictors of SMEs failure. Younger and smaller SMEs seems to be more likely to fail compared to longer existence SMEs due to lack of experience in the business environment and growth development potentials (Abdullah et al. 2014; Altman & Sabato, 2007; Behr & Guttler, 2007; García-Posada & Mora-Sanguinetti 2013; Lugovaskaja 2009; Pervan & Kuvek 2013; Rommer, 2005; Stinchcombe, 1965). The studies that have examined bankruptcy and firm size have established that small size firms fail more often due to internal causes (e.g. operational management problems, inexperienced and incompetent management) while large firms fail mostly due to external causes (environment, competition, demand) (Hall & Young, 1991; Thornhill & Amit, 2003; Wiklund *et al.*, 2010). Similarly, Abdullah et al. (2016) and Altman, Haldeman and Narayanan (1977) highlights that smaller companies have a higher probability of bankruptcy.

Other non-financial variable that are found to be significant predictors include location of company business. Results show that location is an important driver of SME's failure in Germany. The finding show that companies in eastern Germany are substantially riskier than their counterparts in western Germany because of eastern German firms are on average younger, have worse cost structures and operate in a more difficult economic environment (Behr & Guttler, 2007). Likewise in developing countries (for example like Malaysia and Nigeria), regional factor could also make a lot of influence on business success or failure. For example, some states or cities will be much more developed compared to others in terms of

infrastructure, ease of doing business, and business opportunities among other factors.

2.4.3 Corporate Governance Indicators

Corporate governance is a system of rules, practices and processes by which a company is directed and controlled which essentially involves balancing the interests of the many stakeholders in a company - these include its shareholders, management, customers, suppliers, financiers, government and the community (Cadbury, 1992; Deakin & Hughes, 1997; Keasey et al., 1997; Mayer, 1997). A sound and effective governance system in an organisation will have an impact on the long term sustainability of the business. In the early years, corporate governance is arguably not relevant to SMEs because majority of the small businesses are made up of only the owner who is the sole proprietor and manager. SMEs are evident to have less separation of ownership and management than larger firms (Hart, 1995). Though there is a general believe that corporate governance relates more to listed companies and a number of study have modelled business failure prediction models using governance predictors. However, there is global appealing that failure prediction models of SMEs should also incorporate corporate governance indicators (Headd, 2003; McNally & Tophoff, 2014).

For example in Malaysia, Md-Rus et al. (2013) using a sample of government-linked investment companies (GLICs) investigate whether different types of ownership have significant relationship with companies that experienced financial distress. Using logit model, the finding show that ownership by executive directors, family, or all directors are negatively related to the likelihood of distress. Ownership by GLICs and independent directors are not significant in explaining distress while

ownership by domestic private institutional investors is positively significant to financial distress of listed companies. However, the study find that the presence of foreign ownership reduces the likelihood of distress. The existence of foreign owners brings positive impact on performance. It is shown that the higher the percentage of foreign ownership, the better the performance of the company, hence the lower the likelihood of bankruptcy (Douma, George & Kabir, 2006; Md-Rus et al. 2013). The finding support that governance variables such as ownership have significant effect in predicting business failure.

In late 80s, Keasey and Watson (1987) argue that governance factors could as well be useful predictors of small businesses failure in the UK due to high failure of SMEs. Motivated by the study of Argenti (1976) for listed companies using non-financial variables, Keasey and Watson (1987) analyse the effect of number of directors as a predictor of SMEs failure alongside 46 financial ratios using logit method. The sample consists of 73 financially distressed and 73 healthy firms for the period 1970 to 1983. Results show that the number of directors among other variables is negative and significant in predicting business failure among SMEs in the UK. In addition, larger board can decrease the probability of SMEs failure due to increase in monitoring, independent opinions and expertise from different board members. The finding is consistent with that of Abdullah et al. (2016). However, the result is inconsistent with the finding of Ciampi (2015), who find board size to be positively related to business failure. The result supports the agency theory, in which a large number of directors on the board is difficult to run, control and coordinate, while smaller numbers of directors are more involved in efficient and

effective decision-making process (Jensen & Meckling, 1976; Judge & Zeithaml, 1992).

Furthermore, Ciampi (2015) find that CEO-duality is negative and significant in predicting default among SMEs in Italy. The result indicate that presence of CEO-duality will reduce the likelihood of default. If the role is separated, the risk of default increases. The finding give support to the stewardship theorists maintaining that the CEO is not an opportunistic shirker, but basically wants to be a good steward of corporate assets. Therefore, CEO-duality management might be a structural and psychological empowerment of the CEO, as such it encourages the CEO to better serve the firm and its shareholders (Donaldson & Davis, 1991; Kim, Al-Shammari, Kim, & Lee, 2009).

Furthermore, controlling shareholder or majority shareholder is negatively correlated with SMEs default in Italy (Ciampi, 2015). The finding suggests that having a controlling shareholder guarantees stability, lowers conflict levels between owners. However, Abdullah et al. (2016) find that controlling shareholder is positively correlated with SMEs default in Malaysia. They argue that in a situation where ownership concentration exceeded certain limit, controlling shareholder(s) tend to exercise their control rights to generate private benefits, sometimes at the expense of the minority shareholders (Shleifer & Vishny, 1997). Additionally, models that incorporate governance variables combine with financial variables are found to provide a higher predictive accuracy rate (Abdullah et al. 2016; Ciampi, 2015; Keasey & Watson, 1987).

Furthermore, among some of the important characteristics of board is ethnic diversity. Ethnic diversity broadens knowledge, idea and experience through the range of information resources of different cultural background among the board members (Hambrick, Cho & Chen, 1996). An organization with high level of cultural heterogeneity in management able to share ideas and reach ultimate decision based on the various thinking and thus, will improve management performance through a common consensus among the multiracial group of the board. Watson et al. (1993) report that homogeneous board is better in short-term, while heterogeneous board is better in long-term in terms of achieving corporate goals. However, Pelted et al. (1999) find that heterogeneous board results in emotional conflict that ultimately harmed firm performance.

Hofstede (1991) suggest that the two main ethnic groups in Malaysia, the Malays and the Chinese are both low on masculinity but high on power distance. The Malays have high uncertainty avoidance which is reflected by their uneasiness in dealing with ambiguities and uncertainties. This shows that the Malay are more likely to be risk averse in doing business and their firms are likely to have lower risk compared to others races. However, with the current competitive business environment, the firms might also be losing out on business opportunities that could help their firms to grow in the future. Additionally, Malays encourage collectivism, as a result would potentially improve the relationship between manager and employees in an organisation. Thus, a high level of collectivism may indicate that there is a strong communication between the CEO with their subordinates, bringing better cooperation and increasing organisational performance (Triandis, 1993). When CEOs encourage collectivism in their firms, there would be an optimal

communication between leaders and followers, in which followers receive greater support, encouragement and consideration on mission and responsibilities (Graen & Scandura, 1987). This would potentially improve on the firm's performance and reducing the possibility of default.

In contrast, the Chinese are rated as low uncertainty avoidance, willing to accept new challenges and willing to take a greater risk (Haniffa & Cooke, 2000). SMEs managed by the Chinese would probably take up more risk and as a result enjoyed high return from their investments compared to other firms. Furthermore, Chinese are more individualistic (Haniffa & Cooke, 2000). Individualism results in higher innovation; in an individualist culture, individuals have not only a monetary reward from innovation but also a social status reward, and thus, they allocate more labour to innovative activities (Gorodnichenko & Roland, 2011). As a result, firms managed by the Chinese will be having a higher innovation rate which will eventually leads to higher levels of productivity and output in the long run (Gorodnichenko & Roland, 2011).

2.4.4 Macroeconomic Indicators

Companies' sustainability is not only affected by the firm-specific factors but also macroeconomic factors. Business failure prediction studies should consider information about the external environment. The macroeconomic environment may be a significant predictor of business failure (Bhattacharjee et al., 2002; Lehmann, 2003; Richardson et al., 1998; Zavgren, 1983). This is because changes in the macroeconomic environment may worsen the impact of other firm specific factors on bankruptcy risk. For example, factors that may affect a firm's financial health

include interest rate, inflation rate, GDP growth and unemployment rate. Majority of the studies find that macroeconomic variables to be significant predictors of bankruptcy among businesses (Bhattacharjee et al., 2002; Campbell & Choudhury 2005; Cuthbertson & Hudson 1996; Lehmann, 2003; Liu & Pang, 2009; Liu & Wilson, 2002; Swanson & Tybout, 1981; Vlieghe, 2001). More so, these factors are also sources of information that businesses use to provide major decision on their business operations as a whole (Aneta & Anna, 2014; Everett & Watson, 1998; Hudson, 1989; Millington, 1994).

In the case of SMEs for example, Aneta and Anna (2014) empirically examines the usefulness of macroeconomic variables in predicting Polish small business failure. The sample consists of 1547 healthy enterprises and 494 default enterprises covering a period from 2002 to 2012. Using hazard model, the results show that the higher the GDP and unemployment rate the lower the default risk of the companies. GDP growth creates a positive impact on the confidence of businesses, as their profits would gradually increase with economic growth, due to high spending from consumers (Mačerinskienė & Mendelsonas, 2013). In contrast to the finding of Aneta and Anna (2014), Everett and Watson, (1998), Hudson, (1989) and Millington, (1994) report a significant positive relationship between unemployment rate and business failure. High levels of unemployment may be an indicative of a weak economy with decreasing consumer spending and therefore, reduce businesses revenue. Similarly, strong employment growth generally indicates a strong economy with increased consumer spending and thereby increasing businesses revenue.

Everett and Watson (1998) use a sample of 5,196 small business start-ups over the 1961 to 1990 sample period to investigate the effect of external risk factors on small business failure in Australia. The findings show that interest rate is a positive and significant external risk factor to small business failure. This could be as a result of small businesses are more dependent on borrowings to manage their operations. Interest rates would significantly affect the operating costs. The positive association between interest rates and business failure also supports the finding by Hall & Young, (1991), Millington (1994) and Wadhwani (1986).

Furthermore, high rates of inflation may indicate problems in the economy. Wadhwani (1986) argues that *“in the absence of index-linked loans⁹, higher inflation implies higher bankruptcy rates”*. Wadhwani (1986) explores the determinants of UK business failure with quarterly data on total liquidations and find that declining profitability and the nominal interest rate determined aggregate insolvency rates. Having tested with both real and nominal interest rates, Wadhwani interpreted the fact that the nominal interest rate was a highly significant determinant as evidence that inflation had driven corporate liquidations in the study period. When debt is not an index-linked loan, inflation will raise nominal interest charges on the loan. Due to historical cost accounting, inflation tends to distort the company's valuation worsening its financial position and limiting its ability to raise external funds.

⁹ A loan in which payments change in response to changes in an index such as the Consumer Price Index. Indexed loans are usually long-term, since such loans might potentially be affected by many different market factors. One of the most common factors that a loan might be indexed for is inflation, since prices typically rise over time and the principal amount of the loan thus loses value with every time period, benefitting the borrower and hurting the lender. The maturity, interest or principal of an indexed loan may all be adjusted, depending on the structure of the loan. For more detail, please refer to: http://www.investorwords.com/2428/indexed_loan.html#ixzz3v9QheLHy

Moreover, inflation can make an economy and businesses uncompetitive. Businesses would find it difficult to compete in the market especially from foreign competition due to higher prices and higher cost of production and debt-servicing and hence reducing the company's profits and cash flows (Bhattacharjee, Higson, Holly & Kattuman, 2002). Changes in the level of inflation can affect the volatility of cash flows and reduce the firm's ability to pay interests on its debt, thus increasing the risk of financial distress. Empirical finding on UK firms bankruptcy over 1965-1998 presented by Bhattacharjee, Higson, Holly and Kattuman (2002) supports Wadhvani's results that uncertainty in the form of sharp increases of inflation intensified bankruptcy risk.

A more recent study by Salman, Fuchs and Zampatti (2015) using SMEs in the manufacturing sector of Sweden, find that real interest rate shows a significantly positive effect on business failures. A marginal increase of the interest rate variable is found to increase the number of business failures. SMEs in Sweden have relatively limited access to equity market and rely heavily on debt financing. Therefore, companies are expected to be particularly vulnerable, as future returns might not be sufficient to meet fixed obligations from borrowing (Stiglitz, 2000). Consistent with the finding, previous studies have empirically shown that real interest rate has a significant influence on the number of business failures (Cuthbertson & Hudson, 1996; Vlieghe, 2001; Liu, 2004). In brief, studies find that a business failure prediction model that includes financial variables, non-financial variables and macroeconomic variables better predicts business failure than a model that includes only financial and non-financial variables. In view of financial downturn and other economic activities that affect the general economy, financial

institutions such as commercial banks have realized the need to account for macroeconomic variables in business failure prediction models, since the economy has a significant impact on the ability of customers to settle liabilities (Aneta & Anna, 2014).

2.5 Failure Prediction Methods and Accuracy Rates

Generally, studies on business failure utilise MDA, logit model and ANN method to come up with a failure prediction model. This study proposes to use logit model and ANN to predict business failure among SMEs in Malaysia and Nigeria. The choice of these two models is not based on random selection, but on the evidence that they provide a higher predictive accuracy rate compared to other methods used in business failure prediction studies. Moreover, among the conventional statistical methods, logit model is commonly used in predicting business failure because of its advantages over the other conventional methods. On the other hand, ANN has become increasingly popular since it is first used to the finance research area in the early 1990s and is proven to be efficient in predicting business failure. The following sub-section discusses on the approaches.

Table 2.1*Summary of Studies on SMEs*

Author	Country	Method	Year of observation	Predictors type	Firm Industry	Significant Predictors
Edmister (1972)	US	MDA	1954-1969	Financial	Mixed industries	Annual fund flow to current liabilities, equity to sales ratio, working capital to sales ratio, current liabilities to equity, inventory to sales ratio, quick ratio to RMA trend down and quick ratio to RMA up-trend.
Keasey and Watson (1987)	UK	Logit	1970-1983	Financial and non-financial	Mixed industries	Quick ratio, no. of directors, bank floating charge, prior year's qualification, current year qualification.
Cressy (1992)	UK	Logit	1970-1980	Financial and non-financial and macroeconomic	Mixed industries	Net profits to total assets, current asset to current liabilities, net working capital to total assets and net profit relative to total debt.
Lussier (1995)	US	Logit	1995	Non-financial	Mixed industries	Adequacy of start-up capital, record keeping and financial control, industry experience, management experience, business planning, availability of professional advisor, education of owner, quality of staff.
Rommer (2005)	France, Italy and Spain	Hazard	2000-2002	Financial	Mixed industries	Earnings ratio, solvency ratio, loans to total assets ratio, size, age and legal form.
Fidrmuc, Hainz and Malesich, (2006)	Slovakia	Probit & panel probit method	2000-2005	Financial	Mixed industries	Debt to total assets, ROS, EBIT to interest expenses and working capital to EBITDA.
Behr and Guttler (2007)	Germany	Logit	1992-2002	Financial and non-financial	Mixed industries	Equity ratio, growth of equity ratio, return on sales, depreciation ratio, return on sales growth, temporary liquidity problems, size of firms, location of firm head office, business sector and legal form of business.

Author	Country	Method	Year of observation	Predictors type	Firm Industry	Significant Predictors
Blanco, Irimia and Oliver (2007)	UK	Logit	1999-2008	Financial and non-financial	Mixed industries	Legal action by creditors to recover unpaid debts, company filing histories.
Altman and Sabato (2007)	UK	Logit & MDA	1994-2002	Financial	Mixed industries	Legal action by creditors to recover unpaid debts, company filing histories, retained profit to total assets and ratio of total liabilities.
Luppi, Marzo, and Scorcu, (2007)	Italy	Logit	2007	Financial and non-financial	Retail	Debt, cash flows, EBITDA and ROI.
Arslan and Karan (2009)	Turkey	Logit & MDA	2007-2008	Financial	Mixed industries	Inventories to total assets, net profit to total assets and net sales to total assets, expenses to total assets, gross profit margin and net profit margin.
Lugovskaja (2009)	Russia	LDA	2000 – 2004	Financial and non-financial variables	Mixed industries	Current liabilities to total assets, cash to current liabilities, ROA and cash to total assets, current assets to current liabilities, and (cash plus short term debtors) to current liabilities.
Altman et al. (2010)	UK	Logit	2000-2007	Financial and non-financial variables	Mixed industries	Company filing histories, legal action by creditors to recover unpaid debts, comprehensive audit report/opinion data.
Khorasgani (2011)	UK	Logit	2000-2008	Financial	Mixed industries	Leverage ratio, coverage ratio, profitability ratio.
Monelos, Piñeiro and Rodríguez (2011)	Italy	MDA, Logit, & linear multivariate regression	1999-2009	Financial and non-financial variables	Mixed industries	External auditing, average duration of auditors' contracts, rotation, rate of qualified opinion report, and non-observance of duties regarding the publication of financial information.
Sarlija and Jeger (2011)	Croatia	MDA	2006-2009	Financial	Mixed industries	ROE, long term asset to equity plus long term liabilities and equity to sales ratio, leverage ratios, operating revenue to operating expenses, short term liabilities to total asset.

Author	Country	Method	Year of observation	Predictors type	Firm Industry	Significant Predictors
Moscalu (2012)	Romania	MDA	2009-2010	Financial	Manufacturing	Interest expenses to EBIT, quick ratios, overdue payments, profitability, net sales growth rate and taxation rate.
Teti, Dell'Acqua and Brambilla (2012)	Italy	Z-Score model	2009	Financial	Mixed industries	Equity to asset ratio, EBIT to asset, long-term liabilities to asset and sales to asset.
Chotima (2013)	Thailand	Logit	2002–2005	Financial	Manufacturing	Liquidity ratio, leverage ratio and profitability ratio.
Pervan and Kuvek (2013)	Croatia	Logit	2010	Financial and non-financial variables	Mixed industries	Firm age, size measured by number of employees, quality of accounting information, dependence on key customers, firm owners' personal credit performance, and management quality.
Abdullah et al., (2014)	Malaysia	Logit	2000-2010	Financial and non-financial variables	Manufacturing sector	Total liabilities to total assets, earnings before interest, taxes to total assets and firm age.
Aneta and Anna (2014)	Poland	Logit	2002-2012	Financial, non-financial and macroeconomic variables	Mixed industries	Earnings before interest to total asset, taxes to total assets, GDP and unemployment rate.
Ferreira, Grammatikos and Michala (2014)	9 EU countries	Logit	2000-2006	Financial, non-financial and macroeconomic variables	Mixed industries	Earnings before taxes to total assets, EBITDA to interest expenses, cash flow to current liabilities and turnover to total liabilities, and current liabilities to total assets.
Ciampi (2015)	Italy	Logit	2010-2011	Financial and governance variables	Mixed industries	CEO-duality, presence of outside directors, board size and ownership concentration.

2.5.1 Multiple Discriminant Analysis

The multiple discriminant analysis (MDA) and logit models are the most common and popular statistical models to predict failure among listed companies and small businesses. However, authors have subsequently pointed out some violations in the basic assumptions of the MDA when the model is applied to predict business failure. First, the standardized coefficients of the MDA do not indicate the relative importance of the different independent variables used. The output of the application of an MDA model is a score which has little intuitive interpretation since it is basically an ordinal ranking (discriminatory) approach and cannot be interpreted like the slopes of a regression equation (Ohlson, 1980).

A second assumption which needs to be tested prior to the development of the MDA model is the assumption of equal dispersion matrices. If this assumption is violated, the significant test for mean differences between the failing and non-failing group of firms will be affected. Furthermore, in case of unequal dispersion matrices, a quadratic classification rule – a quadratic MDA model – needs to be used (Joy & Tollefson, 1975; Eisenbeis, 1977; Zavgren, 1983). In practice, however, researchers avoid working with quadratic MDA model because this model is complex and only outperform the linear MDA model in the case of (1) a large sample, (2) a small number of independent variables relative to the sample and (3) substantial differences in the dispersion matrices. In fact, what the quadratic MDA model is trying to do is to transform the data in a way that the dispersion matrices are not too different from linear MDA (Taffler, 1982).

Third assumption relates to the distributional properties of the predictors. The variance-covariance matrices of the predictors should be the same for both groups, the failed and non-failed firms. The independent variables have to be multivariate normal (Ohlson, 1980). However, in practice, the assumption of multivariate normality is often violated (Deakin, 1976; Taffler, 1977; Balcean & Ooghe, 2004; Barnes, 1987) that may lead to potential bias in the significant test and the estimated error rates (Altman & Loris, 1976; Eisenbeis, 1977; McLeay & Omar, 2000; Richardson & Davidson, 1984). Besides, a requirement of normally distributed predictors certainly exclude the use of dummy independent variables (Ohlson, 1980). Richardson and Davidson (1983) find that if the assumption of independent variables being multivariate normal is violated, the model would be sensitive to the data used in the estimation of parameters.

The fourth assumption states that, in the selection of the optimal cut-off score of the estimated model, the prior probabilities of belonging to the failing or non-failing group (i.e. population) and the costs of a type I and a type II error should be considered (Edmister, 1972; Eisenbeis, 1977; Deakin, 1977; Zavgren, 1983; Steele, 1995). If this restrictive assumption is violated, the reported accuracy of the MDA model will be biased and will not indicate the accuracy of the model when applied to the total population. In this respect, Deakin (1977) points out that the specification of prior probabilities and misclassification costs are required in order to get an accurate image of the frequency of errors likely to be obtained in a 'real world' application of the model. The optimal cut-off point should result from the minimization of a 'total loss function', which includes the error rates and both the corresponding population proportions and misclassification costs.

However, in practice, the specification of the error costs seems to be a very subjective decision. The costs of the consequences relying on both types of errors are mainly intangible and immeasurable and depends on the risk behaviour of the decision-maker and his or her attitude towards the proportion of the cost factors. In addition, the specification of population proportions seems to be very difficult and subjective, as a certain reference period needs to be chosen. This is often called subjective factor (Steele, 1995). Due to these practical problems, most researchers applying MDA simply try to minimize the total error rate instead of the total loss function.

2.5.2 Logit Model

Based on the limitations of MDA, the practical benefits of the logit method is that; it does not require the restrictive assumptions of MDA and it allows working with disproportional samples that do not require multivariate normal distributed variables. From a statistical point of view, logit regression seems to fit well with the characteristics of default prediction problem, where the dependant variable is binary (default/non-default) and with the groups being discrete, non-overlapping and identifiable. Logit analysis incorporates non-linear effects, and uses the logistical cumulative function in predicting a bankruptcy (Laitinen & Kankaanpaa, 1999).

Furthermore, the logit model yields a score between zero and one which conveniently gives the probability of default to each company in a sample (Ohlson, 1980; Ooghe et al., 1993). The estimated coefficients can be interpreted and see the relative importance or significance of each of the independent variables in the explanation of the estimated probability of default (Mensah, 1984; Ohlson, 1980;

Zavgren, 1983). Logit models allow for qualitative variables with categories in addition to continuous data. In this case, dummies can be used (Ohlson, 1980; Keasey & Watson, 1987; Joos et al, 1998).

Ohlson (1980) applies logit model to predict business failure of 105 bankrupt firms and randomly chosen 2,058 non-bankrupt firms over the 1970 to 1976 sample period, using only the financial ratios. Ohlson's logit model classification accuracy achieves a 96.3 percent. Since the work of Ohlson (1980), subsequent studies have shown that logit model is empirically superior to MDA in both classification and prediction accuracy. Lau (1987) uses multinomial logit analysis (MLA) and MDA to compare the predictive accuracy of each method. The results showed that MLA outperformed MDA. The author reported an overall 96 percent predictive accuracy rate for the model that used one year before default data, 92 percent predictive accuracy rate for the model that used two years before default data and 90 percent predictive accuracy rate for the model that used three years before default data. Pindado and Rodrigues (2005) compare the predictive ability between MDA and logit model using 84 small Portuguese firms from the footwear manufacturing industry. The empirical results show that the classification accuracy for MDA model is 89.58 percent, while logit model is 91.67 percent when the estimation sample is used. This finding is consistent with the result of Gentry et al. (1985), Laitinen and Kankaanpää (1999), Lennox (1999) and Platt and Platt (1990) who find that the logit model outperform the MDA. Altman and Sabato (2007) show that logit model performs better with a predictive accuracy rate of 87.22 percent compared to MDA model with a 59.87 percent accuracy rate. They conclude that logit model performs better in discriminating the failed and non-failed companies than the MDA.

Furthermore, in Theodossiou's (1991) three statistical techniques, namely the linear probability model, the logit model and the probit model, were compared to identify the one with the most appealing performance in predicting bankruptcy in Greece. The results show that all three models were successful in predicting bankruptcy with an accuracy rate over 90 percent. However, both logit and probit models were superior to the linear probability model. Similar to Theodossiou's research (1991), Lennox's study (1999) examine bankruptcy for the UK companies using MDA, logit, and probit model. Results show that the probit and logit models outperformed the discriminant model. Similarly, Šarlija (2002) uses logistic regression, decision trees and neural networks to predict bankruptcy on a sample of 200 loan applications. The best model of credit default on this study was logistic regression with 83 percent of correct classification. Different models of ANNs (from 44% to 69%) and decision tree (from 44% to 79%) had lower predictive ability. Moreover, Darayseh et al. (2003) develop a logit model for bankruptcy prediction for a group of 110 manufacturing firms that went bankrupt between 1990 and 1997 which were matched by 110 non-bankrupt firms according to total assets and industry classification. Their estimated model could make correct predictions of 87.8 percent and 89.5 percent for the in-sample and holdout samples for 1 year prior to bankruptcy.

Sajter (2008) develops a bankruptcy prediction model for a sample of 72 healthy and 18 bankrupt companies from four counties in the eastern Croatia. The logit model has a higher predictive accuracy rate of 90 percent compared to the MDA model, which carries 50 percent accuracy rate. Similarly, when Sirirattanaphonkun

and Pattarathammas (2012) develop a failure prediction model for the Thailand's SMEs using MDA and logit model, the finding shows that logit model outperform MDA. Their observation period covers from year 2000 to 2010. The result shows that the logit model reports a higher predictive accuracy rate of 85.5 percent for the out-of-sample test, while MDA reports only 81 percent. However, Collens and Green (1982), Hamer (1983), and Press and Wilson (1978) compared the performance of the logit model and the MDA model in predicting bankruptcy and find that the explanatory power of the logit model is similar to that of MDA. Though the MDA model is found to be as accurate as the logit model, the logit model is still more popular than the MDA because of the improved statistical validity.

2.5.3 Artificial Neural Network

Recent studies in artificial neural networks (ANN) show that ANN are powerful tools for pattern recognition and pattern classification due to their nonlinear, nonparametric adaptive-learning properties (Murtaza & Shah, 2000). ANN is a form of soft computing method, which is modelled like the human brains (Coates & Fant, 1993; Zhang et al., 1999). ANN is non-parametrical model that does not rely on specific assumptions related to the distribution of predictors or properties of data. ANN is able to accurately classify groups of businesses based on companies financial and/or operating health, with results that are very close to, or in some cases even better than the discriminant analysis (Altman, Marco & Vareto, 1994). ANN can also better deal with missing data, outliers, and multicollinearity than regression (Coates & Fant, 1993; Zhang et al., 1999).

The first attempt to use ANNs to predict bankruptcy is made by Odom and Sharda (1990). In their study, three-layer feed-forward networks were used and the results are compared to those of MDA model. Using different ratios of bankrupt firms to non-bankrupt firms in training samples, they test the effects of different mixture levels on the predictive capability of neural networks and discriminant analysis. A comparison of the results from the models' predictions for the holdout subsample with the 50/50 training set shows that the discriminant analysis has a correct prediction rate of 59.26 percent for the bankrupt firms which is well below the correct prediction rate of 81.4 percent for the neural network.

When the training sample was changed to the 80/20 proportion of non-bankrupt to bankrupt firms, the discriminant analysis had a correct prediction rate of 70.37 percent for the bankrupt firms compared to the neural network's correct prediction of 77.78 percent. Furthermore, when the 90/10 sample was used for the training sample, the neural network did better correctly predicting 85.71 percent of the holdout subsample, while the discriminant analysis method predicted only 78.57 percent. The neural network appears to be more robust, performing better than the discriminant analysis method in the different levels. It also appears to be more consistent than the discriminant analysis method. Since the work of Odom and Sharda (1990), researchers have tried to use ANN in business failure prediction due to the reported efficiency of the method. Coats and Fant (1993) and Wilson and Sharda (1994) compare the results of multiple discriminant analysis against the neural network approach and their results suggest that the ANN approach is more effective than MDA in classifying distressed and non-distressed firms. The predictive accuracy rate for one year prior to failure is 95.0 percent for the ANN with MLP model, and 87.9 percent for the MDA model.

Tam (1991) uses back-propagation neural networks (BPNN) model which is a multi-layer perceptron (MLP) model. The study predict bank failures in a sample of commercial banks in Texas for one year and two years prior to failures. The input variables are the capital, asset, management, equity and liquidity (CAMEL). The study finds that BPNN outperforms (with predictive accuracy rate of 95.9%) all other methods, such as discriminant analysis (with predictive accuracy rate of 84.7%) and logit model (predictive accuracy rate of 87.3%), in terms of their predictive accuracy. Subsequently, Tam and Kiang (1992) compare the power of linear discriminant analysis (LDA), logit, feed-forward neural network and BPNN on bank failure prediction problems. The finding show that BPNN (with predictive accuracy rate of 96.2%) outperforms the other techniques for a one-year-prior to bankruptcy training sample, while LDA (with predictive accuracy rate of 94%) outperform the others for a two-year-prior to bankruptcy training sample. However, for holdout samples, BPNN outperform the others methods for one-year-prior to bankruptcy sample with predictive accuracy rate of 85.2% while LDA (with accuracy rate of 92.5%) has the highest accuracy rate for two-year-prior to bankruptcy samples. In the jackknife method¹⁰, BPNN also outperform the LDA and logit model in both the one-year-prior to bankruptcy and the two-year-prior to bankruptcy holdout samples. In all, they conclude that neural network outperform the LDA and logit method.

¹⁰ In statistics, the jackknife is a resampling technique especially useful for variance and bias estimation. The jackknife predates other common resampling methods such as the bootstrap. The jackknife estimator of a parameter is found by systematically leaving out each observation from a dataset and calculating the estimate and then finding the average of these calculations.

Neophytou et al. (2001) aim at developing a failure prediction model for UK industrial companies using logit analysis and ANN using a dataset of 51 matched-pairs of failed and non-failed firms over the period 1988 to 1997. The finding from their analysis show that ANNs provide a higher overall classification results for the first and third year when compared to the logit model (95.83% vs. 93.75% and 75% vs. 69.44% respectively), while the classification for the second year remains the same at 84.09 percent. Furthermore, ANN also reduce significantly the type I error for the three years prior to bankruptcy sample. Type II error, however, increases for the one year and two year prior to bankruptcy sample, while it remains the same for the three year prior to bankruptcy sample (27.8%). They conclude that ANN were proved to be superior as they provided the highest prediction results in all three years prior to insolvency.

Moreover, Park, (2005) compare the predictive accuracy of ANN and logit model in a hospitality industry. The finding show that ANN obtained a higher accuracy rate compared to the logit model in an in-sample test as well as in holdout (testing) sample test. ANN analysis showed that the trained neural network model achieved 92.9 percent estimated accuracy rate while that of logit is 91.3 percent. This was slightly higher than the accuracy rate achieved by the logit model. In the testing (holdout) sample test, the ANN model confirmed the validity of the trained model with 87.5 percent accuracy rate (while logit is 83.3%) associated with 12.5 percent Type-I error and zero percent Type-II error. It is noteworthy that not only did neural network achieves a higher overall accuracy rate than the logit model from in-sample test as well as from holdout test, but the higher accuracy rate was attained by lowering the Type-I error, or misclassification of failed firms. Since Type-I error

involves much higher costs than does Type-II error (Lee et al., 2005), it could be inferred that ANN models are a more sophisticated tool when used for classification tasks than are a logit model. The result confirmed previous assertions made by many researchers stating the superiority of neural network over logit models in classification and prediction tasks.

Ciampi, Vallini, and Gordini (2009) finding show that ANN increases the predictive accuracy to 68.4 percent compared to MDA (65.9%) and logit (67.2%), indicating that ANN is a better approach to predict default among small enterprises. Their finding is consistent with that of Fletcher and Gross (1993) where ANN has a predictive accuracy of 91.7 percent compared to logistic regression with 85.4 percent accuracy rate. Accordingly, Zhang, Patuwo, and Indro, (1999), Cadden (1991), Odom and Sharda (1990), Salchenberger, Cinar and Lash (1992), Shin and Lee (2002), Zhang, Hu and Patuwo (1999) reported that ANN provides a higher predictive accuracy rate compared to the logit model.

2.6 Summary

The purpose of this chapter is to study some theoretical background and previous research on revolution of bankruptcy prediction study to serve as a reference and the fundamental of the prediction of bankruptcy among SMEs in Malaysia and Nigeria. Over the last 40 years, academic studies have been searching for an efficient business failure prediction model. Most of the existing studies incorporate financial and non-financial indicators in the SMEs failure prediction models. However, there are a few studies that include corporate governance and macroeconomic indicators in the prediction models, with evidence from the developed countries. Given that

financial ratios have been dominant in most research to date, increasing the categories of explanatory variables such as corporate governance structures, management practices and macroeconomic indicators would add value to the failure prediction model.

The chapter discusses the different statistical models have been employed in the effort of developing a more accurate failure prediction model. Existing literature show that MDA, logit and ANN seems to be most popular methods; and each method has its own specific assumptions, advantages and disadvantages. The predictive accuracies of different models seem to be generally comparable, ANN models perform marginally better than traditional models such as logit and MDA. Individually, the use of multiple discriminant analysis (MDA) and logit models dominates the research but empirical evidence show that logit model is more accurate in predicting failure than MDA. The following chapter, chapter three will focus on the research methodology to test the hypotheses developed.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The identification of bankruptcy provides stakeholders with the opportunity to take pro-active measures to prevent bankruptcy of a company. This chapter explains and justifies the data and sample firms selected and the time period during which the investigation is carried out. The chapter also presents the theoretical framework of the study as well as the methodology used to test the hypotheses and develop the bankruptcy prediction models.

3.2 Data Collection and Sample Selection

The main objective of this study is to identify the relevant financial, non-financial, corporate governance and macroeconomic indicators in predicting bankruptcy among SMEs in Malaysia and Nigeria. This study examines and compares the predictive accuracy rate of the bankruptcy prediction model developed using the logistic regression and artificial neural network (ANN) methods. The sample firms, which include bankrupt and non-bankrupt SMEs in the manufacturing sector, are collected from the Companies Commission of Malaysia (SSM)¹¹ and the Corporate Affairs Commission (CAC)¹² of Nigeria. The SSM and CAC provides corporate

¹¹ An autonomous body that function as a one-stop centre for corporate information, regulation and development of conducive business environment.

¹² The Corporate Affairs Commission Nigeria was established by the Companies and Allied Matters Act, which was promulgated in 1990 to regulate the formation and management of companies in Nigeria. "The functions of the Commission as set out in section 7 of the Companies and Allied Matters Act, includes the following: 1. to administer the Act, including the regulation and supervision of the formation, incorporation, management and winding up of companies. 2. Arrange and conduct an investigation into the affairs of any company where the interests of the shareholders and the public so demand and undertake such other activities as are necessary or expedient for giving full effect to the provisions of the Act. The establishment of the Corporate Affairs Commission as an autonomous body was as a result of the perceived inefficiency and ineffectiveness of the former

information such as companies' profile information, the balance sheets and income statements among others records of all Malaysian and Nigerian companies.

Most studies define bankruptcy from the legal perspective (Abdullah et al., 2014; Altman and Sabato, 2007; Charitou, Neophytou & Charalambous, 2004) as it provides an objective criteria that allows researchers to easily classify the sample of firms to be examined. The sample of Malaysian SMEs are selected based on the SME's definition adopted by the National SME Development Council as discussed in earlier chapter. Bankrupt companies are selected as classified under the winding up by Court Order under Part IV Cessation of Companies, Section 465 of (1) (e) or winding up by Creditors Request under Section 450 of (1) of Malaysian Companies Act 1965 as Amended 2016. The definition by the National Policy on SME (see table 1.2) is used to select Nigerian SMEs sample and winding up by Court Order under Section 408 (d) of The Companies And Allied Matters Act, LFN 2004 of Nigeria is used to select bankrupt companies. Furthermore, the SMEs' profile and other firm-specific variables are collected from the financial statements of the SME. On the other hand, macroeconomic indicators are available from Thomson Reuters Datastream. This study covers a period of 15 years, starting from year 2000 to 2014.

The samples are selected by a way of two-step process. For the case of Nigeria, the first step is to take the entire population of Nigeria SMEs recorded in the CAC that operated in the manufacturing sector and have been winding-off between 2000 and 2014. In this regards, there are 4,058 companies of which 630 companies were

Company Registry, a department within the Federal Ministry of Commerce and Tourism which was then responsible for the registration and administration of the repealed Companies Act of 1968 (CAC, 2016)". For more detail on CAC and its functions, please refer to <http://new.cac.gov.ng/home/about-us/>

winding up based on court order, 1,560 were voluntarily wind up and 1,868 companies were struck off. As mentioned earlier, the selection of bankrupt SMEs that are included in the sample are those winding up based on court order under Section 408 (d) of The Companies and Allied Matters Act, LFN 2004 of Nigeria and further classify as small or medium enterprise based on the definition adopted by the National Policy on SME (refer to table 1.2). After applying the above definitions, and strictly going through the companies' financial data and other corporate information to check on the availability of data, the final sample for the bankrupt SMEs is 316.

Majority of the bankruptcy prediction studies have been based on one year before the bankruptcy event. However, models developed on data several years before eventual bankruptcy might well provide more informational value to interested parties. The prediction of bankruptcy only 1 year before bankruptcy might prove too late for undertaking actions such as the extraction of cash by an investor, or the execution of a turnaround plan. In order to take effective measures, bankruptcy needs to be predicted a few years in advance. Therefore, this study obtained three years of data prior to the date of bankruptcy. Each report is to include the balance sheet, income statement, director's information, list of shareholders and their respective holdings and corporate profile (which include date of incorporation, business location among other information). The breakdown of the final bankrupt sample is 172 SMEs for 3-year prior to bankruptcy sample, 86 SMEs for 2-year prior to bankruptcy sample and 58 SMEs for 1-year prior to bankruptcy sample. As observed, the more we move closer to the bankruptcy date, the less number of sample of bankrupt firms as most of them were unable to submit their financial

reports, which led to a smaller sample for the years closer to bankruptcy. Three hundred and fourteen of the firms were eliminated because of missing data in some years. Furthermore, all the reports of the selected SMEs are retrieved from the CAC library manually. Since the study is confined to manufacturing firms only, the sample of the bankrupt SMEs represents 50.2 percent of the population of the bankrupt manufacturing firms over the research period.

Consistent with the majority of previous studies on bankruptcy prediction, companies are matched based on the closest total assets, in which a bankrupt SME is matched with a healthy SME. Matching sample is necessary because if non-bankrupt firms are to be drawn at random, there would probably be substantial differences between the two groups (Jones, 1987). Therefore, the second step was to select a pair sample of firms which are non-bankrupt during the study period to correspond with the number of bankrupt SMEs in the same sector. The selection is done with the aim to obtain a sample firm of an almost similar size (total asset) and identical composition of the sample of bankrupt firms. Consequently, after classifying the firms as small or medium enterprise based on the definition adopted by the National Policy on SME and based on the availability of data, 316 non-bankrupt SMEs were matched with the bankrupt SMEs which gave a total of 632 SMEs that are used in the analysis. The breakdown of the sample is presented in table 3.1 (of which 344 for 3-year prior to bankruptcy sample, 172 for 2-year prior to bankruptcy sample and 116 for 1-year prior to bankruptcy sample).

The same two-step process is used in the selection of Malaysian sample. The list of all SMEs which operated in the manufacturing sector that wind up between 2000

and 2014 was retrieve. The record shows that there are 2,164 companies that go bankrupt of which 1,284 companies are wind up based on court order, 51 companies are wind up based on creditor's request, 209 are voluntarily wind up by Members and 620 companies are strike off. In order to achieve the objectives of this study, the selection of bankrupt SMEs that are included in the sample are those winding up based on court order and creditors request. The winding up by Court Order is under Part IV Cessation of Companies, Section 465 of (1) (e) while by winding up by Creditors Request is under Section 450 of (1) of Malaysian Companies Act 1965 as Amended 2016. Additionally, apart from the legal definition, the firm has to be further categorised as small or medium enterprise based on the definition adopted by the National SME Development Council (NSDC) (refer to table 1.3) before being selected. Subsequently, after going through the companies' financial data, other relevant information and availability of data, the final sample of the bankrupt SMEs is 778. The selected companies represents 333 SMEs for 3-year prior to bankruptcy sample, 235 SMEs for 2-year prior to bankruptcy sample and 210 SMEs for 1-year prior to bankruptcy sample. Five hundred and six companies are deleted because of non-availability of data. The sample of the bankrupt SMEs represents 60.6 percent of the population of the manufacturing firms over the research period.

Similarly, 778 non-bankrupt SMEs are matched with the bankrupt SMEs following a similar approach for Nigerian sample which is based on closest total asset (size) and industry. The total sample SMEs are 1,556, representing 666 SMEs for 3-year prior to bankruptcy sample, 470 SMEs for 2-year prior to bankruptcy sample and 420 SMEs for 1-year prior to bankruptcy sample as shown in table 3.1. The dataset is split into two groups, the training set and the validation set.

Table 3.1

Summary of the sample selection

Sample Years	Total Sample	Training Sample	Validation Sample (Holdout sample)
Malaysia			
1-year prior sample	420	336	84
2-year prior sample	470	376	94
3-year prior sample	666	534	132
Nigeria			
1-year prior sample	116	94	22
2-year prior sample	172	138	34
3-year prior sample	344	276	68

As shown in table 3.1, the training sample is used to build the bankruptcy model. To be consistent with majority business failure prediction studies, twenty percent of the total sample is retained as the holdout sample in order to test the prediction models' performance in predicting bankruptcy (Abdullah et al., 2016; Abdullah et al., 2014; Altman & Sabato, 2007; Charitou et al., 2004). Validation is important to avoid over-fitting problem implying that the model fits the training data well (Kwon, 1997). Prior studies also used the holdout sample to test on the robustness of bankruptcy model (Abdullah et al., 2016; Abdullah et al., 2014; Altman & Sabato, 2007; Charitou et al., 2004).

3.3 Research Framework

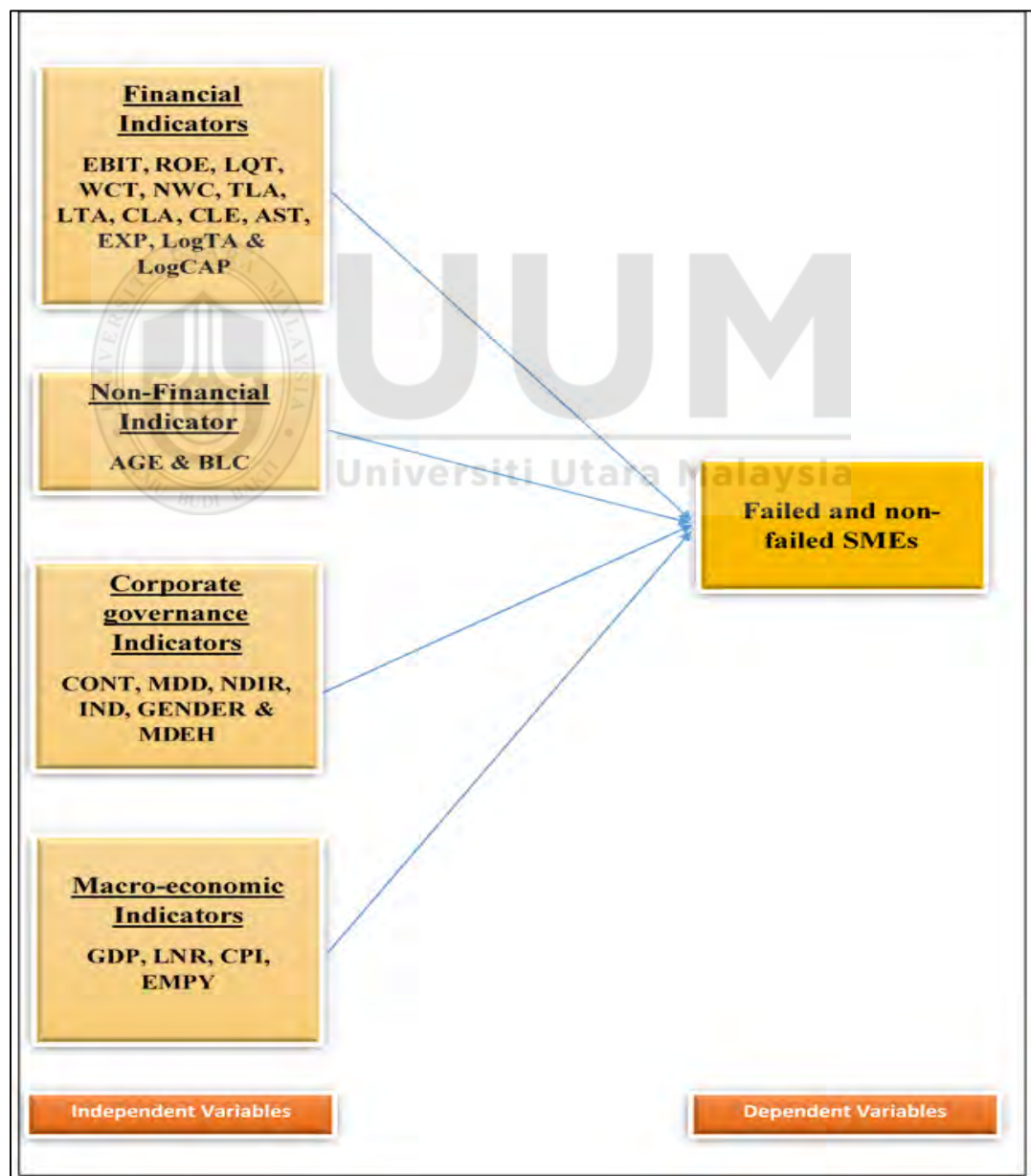
A list of 25 variables are identified for the purpose of this study. The selection of the majority of these variables is on the basis of their popularity in the literature and their predictive success in previous research of SMEs bankruptcy prediction while a few of the variables are selected on a theoretical basis. The reason for the arbitrary choice of variables is that the theoretical basis for the selection of variables in bankruptcy prediction studies has always been too limited (Karels & Prakash, 1987;

Dirickx & Van Landeghem, 1994). Furthermore, some of the variables are left out due to non-availability of data. For example, family ownership is excluded as this information is not available. SMEs in both Malaysia and Nigeria are not required to disclose such information. Variables related to interest expenses are also excluded as the information is not available from the SSM database. As depicted in Figure 3.1, the dependent variable is the financial distress status of the SME (STATUS). If the SME is bankrupt firm, then STATUS is coded as 1, otherwise STATUS is coded 0 if the SME is healthy.

The independent variables are grouped into four categories including financial, non-financial, governance and macroeconomic indicators as presented in Figure 3.1 and the measurement of each variable is provided in table 3.2. The objective is to identify the set of significant predictors of SMEs bankruptcy in Nigeria and Malaysia. The financial variables include earnings before interest and tax to total asset (EBIT), return on equity (ROE) as measure for “profitability”; current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), as measure for “liquidity”; total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE) as measure for “leverage”; asset turnover (AST), selling, general and administrative expenses to sales (EXP) as measure for “efficiency”. Logarithm of total assets (LogTA) and logarithm of share capital (LogCAP) as proxy for “size”.

The non-financial variables as seen in figure 3.1 include AGE as a measure of firm years in business and location of business (BLC). Corporate governance variables

includes controlling shareholder (CONT) as a measure for “ownership structure”; number of directors in the board (NDIR), board independence (IND) measure using independent directors in the board, managing director duality (MDD), gender of managing director (GENDER), ethnicity of managing director (MDEH) as measures for “board structure”. The macroeconomic variables includes growth in gross domestic product (GDP), lending rate (LNR), consumer price index (CPI) and unemployment rate (EMPY) as measures for “macroeconomic condition”.



Earnings before interest and tax to total asset (EBIT), return on equity (ROE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), total liabilities to total assets (TLA),

long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director (MDEH), yearly percentage changes gross domestic product (GDP), yearly percentage changes lending rate (LNR), yearly percentage changes consumer price index (CPI) and yearly percentage changes unemployment rate (EMPY).

Figure 3.1
Theoretical research framework

3.4 Hypotheses Development

The hypotheses tested in this study are developed based on the research problems and objectives. Reference to the research framework presents in figure 3.1, this study hypothesise that SMEs bankruptcy prediction models should include both financial, non-financial, corporate governance and macroeconomic indicators in order to improve bankruptcy prediction accuracy rates. The following section provides the detail of the variables.

3.4.1 Financial Indicators

There are thirteen financial indicators which are grouped in five categories of variables used in this study. The financial indicators are included in order to develop the bankrupt prediction models. The variables are as follows:

Table 3.2

Definition of variables

Variable	Category	Measurement	Cited by
EBIT	Financial	Ratio of EBIT to total asset	Abdullah et al., (2014); Partington, Russel, Stevenson, and Torbey (2001).
ROE	Financial	Ratio of net income to total equity	-
LQT	Financial	Ratio of current asset to current liabilities	Abdullah et al., (2014); Arslan and Karan (2009); Chotima, (2013), Fidrmuc, Hainz and Malesich, (2006); Monelos et al., (2012); Moscalu (2012); Sirirattanaphonkun and Pattarathammas (2012).
WCT	Financial	Ratio of working capital to total debt	Mine and Hakan, (2006)
NWC	Financial	Current asset minus current liabilities	Teti et al., (2012)
TLA	Financial	Ratio of total liabilities to total asset	Abdullah et al., (2014); Behr & Guttler (2007); Kornell & Wallin (2011); Luppi, Marzo, & Scorcu, (2007); Monelos et al., (2012); Pederzoli & Torricelli (2010); Pervan & Kuvek, (2013); Sirirattanaphonkun & Pattarathammas, (2012); Teti, Dell'Acqua & Brambilla, (2012).
LTA	Financial	Ratio of long-term debt to total asset	-
CLA	Financial	Ratio of current liabilities to total assets	Abdullah et al., (2014); Chotima, (2013); Ferreira et al., (2014); Lugovskaja, Edmister (1972)
CLE	Financial	Ratio of current liabilities to equity	Ferreira et al., (2014)
AST	Financial	Asset turnover ratio	Florackis (2008), Huang, Wang and Wang (2015), Pan (2015), Sign and Davidson (2003) and Zheng (2013)
EXP	Financial	Ratio of selling, general and administrative expenses to sales	

Variable	Category	Measurement	Cited by
LogTA	Financial	Logarithm of total assets.	Abdullah et al., (2014); Abdullah et al., (2016)
LogCAP	Financial	Logarithm of share capital.	Abdullah et al., (2014); Abdullah et al., (2016)
AGE	Non-financial	Years of firm business operations.	Abdullah et al., (2014); Abdullah et al., (2016); Altman et al., 2010); Blanco et al., (2010); Keasey and Watson, (1987).
BLC	Non-financial	Dummy variable which takes the value of 1 if the firm business location is in industrialised region, 0 otherwise.	Behr & Guttler (2007)
CONT	Governance (ownership)	Dummy variable which takes the value of 1 if the firm has one shareholder holding 33 percent or more of the outstanding shares, otherwise 0	Security Commission Malaysia, (2013).
MDD	Governance (ownership)	Dummy variable which takes the value of 1 if the firm MD is also chairman of the board or part of the shareholders, 0 otherwise.	Ciampi, 2015; Elloumi and Gueyié (2001); Parker et al. (2002).
IND	Governance (ownership)	Proportion of independent directors on the board at the end of the year	Cornett, McNutt & Tehranian, (2009); Hay, Knechel & Wong, (2006); Lu, Xu, & Liu, (2009); Markel, Mather & Ramsy (2006); Xie, Davidson & DaDalt, (2000)
NDIR	Governance (board structure)	Measure of number of directors in the board structure of the firm at the end of the year.	Abdullah et al., (2016); Chaganti, Mahajan, and Sharma (1985); Ciampi, (2015); Deng and Wang (2006); Dowell et al. (2011); Goodstein, Gautam, and Boeker (1994); Keasey and Watson, (1987);
GENDER	Governance (board structure)	Dummy variable which takes the value of 1 if the firm's Managing director is male and 0 otherwise.	Abdullah et al., (2016)

Variables	Categories	Measurement	Cited by
MDEH	Governance (board structure)	Dummy variable which takes the value of 1 if the firm's Managing director is Malay and 0 otherwise (Chinese or Indian).	-
GDP	Macroeconomic	Yearly percentage changes in GDP growth.	Aneta and Anna (2014)
LNR ¹³	Macroeconomic	Yearly percentage change in lending rate	Everett & Watson, (1998); Hall & Young, (1991); Pankki, (2013); Peterson, Kozmetsky, & Ridgway (1983)
CPI	Macroeconomic	Yearly percentage changes in consumer price index	Everett & Watson, (1998); Jabeur, (2014); Millington, (1994); Wadhwani, (1986)
EMPY	Macroeconomic	Yearly percentage change in unemployment rate	Everett & Watson, (1998); Hudson (1989); DiPietro & Sawhney (1977)
Earnings before interest and tax to total asset (EBIT), return on equity (ROE), return on assets (ROA), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director (MDEH), gross domestic product (GDP), lending rate (LNR), consumer price index (CPI) and unemployment rate (EMPY).			

¹³ Many interest rates coexist in an economy, reflecting competitive conditions, the terms governing loans and deposits, and differences in the position and status of creditors and debtors. In some economies interest rates are set by regulation or administrative fiat. In economies with imperfect markets, or where reported nominal rates are not indicative of effective rates, it may be difficult to obtain data on interest rates that reflect actual market transactions.

The study used lending rate of World Bank. Lending rate is the bank rate that usually meets the short- and medium-term financing needs of the private sector. This rate is normally differentiated according to creditworthiness of borrowers and objectives of financing. Deposit and lending rates are collected by the International Monetary Fund (IMF) as representative interest rates offered by banks to resident customers in their respective countries. For more information, please see <http://www.imf.org/external/pubs/ft/mfs/manual/index.htm>

3.4.1.1 Profitability Ratios

Profitability measures is regarded as one of the major determinant of bankruptcy for small firms. Profitability as specified in the framework is measured by the ratio earnings before interest and tax to total asset (EBIT) and return on equity (ROE). EBIT is an indicator of how profitable a company is relative to its total assets, revealing how efficient management is at using its assets to generate earnings. The higher the ratio, the better the company is utilizing its asset efficiently in generating profits. Since a firm's ultimate existence is based on the earning power of its assets, earnings before interest and tax to total asset measure continually outperform other profitability measures (refer to section 2.4.1 on review of profitability measures) in assessing the risk of bankruptcy (Altman et al., 2010). ROE as the second profitability measure used in this study reveals how much profit a firm generates with shareholders' investment. Shareholders wants to see high return on equity ratio because this shows the company's management ability to generate income from the amount invested by shareholders.

Pecking order theory maintains that businesses with high level of profitability adhere to a hierarchy of financing sources and prefer internal financing (at zero cost issuance as compare to other sources like debt or equity), and debt is preferred over equity if external financing is required (Myers, 1984). In the context of SME, the implication is that the less profitable an SME is, the more it needs to depend on short-term and/or long-term debt to finance its assets and business activities. Furthermore, profitable SMEs face lower bankruptcy probabilities. Firms are able to meet their short and long term commitments while unprofitable SMEs are likely not be able to meet the firm's financial obligations (Arslan & Karan 2009; Chotima,

2013; Fidrmuc et al., 2006; Fidrmuc & Hainz 2010; Khorasgani, 2011; Lugovskaja, 2009; Monelos et al., 2011; Monelos et al., 2012; Moscalu 2012; Sirirattanaphonkun & Pattarathammas 2012). Therefore, this study expects a negative relationship between profitability and bankruptcy.

H1: There is a negative relationship between profitability and bankruptcy.

3.4.1.2 Leverage Ratios

MM proposition II argues that as company gears up by replacing equity with debt, it shields more from corporate tax. As such company should be financed entirely by debt. At a high level of gearing, there is a possibility that a company is unable to meet its interest commitment and, hence it increases the risk of bankruptcy. The optimization of capital structure involves a trade-off between the present value of the tax rebate associated with a marginal increase in leverage and the present value of the marginal cost of the disadvantages of leverage (Robichek & Myers, 1965). In other words, higher level of leverage will result in the trade-off between interest tax shield and bankruptcy risk (Hirshleifer, 1966; Kraus & Litzenberger, 1973; Robichek & Myers, 1965). Furthermore, at a higher level of gearing, shareholders would require a higher rate of return to compensate them for taking up higher financial risk (Hirshleifer, 1966; Kraus & Litzenberger, 1973; Robichek & Myers, 1965).

SMEs rely heavily on short-term and long-term liabilities to finance their day-to-day business operations. They often rely on trade finance from suppliers when bank finance is not available to them (Altman et al. 2010). Leverage is found to be a positive and significant predictor of bankruptcy of SMEs (Abdullah et al., 2014;

Behr & Guttler 2007; Chotima, 2013; Ferreira, Grammatikos & Michala, 2014; Kornell & Wallin 2011; Lugovskaja, 2009; Luppi, Marzo, & Scorcu, 2007; Monelos et al., 2012; Pederzoli & Torricelli 2010; Pervan & Kuvek, 2013; Sarlija & Jeger, 2011; Sirirattanaphonkun & Pattarathammas, 2012; Teti, Dell'Acqua & Brambilla, 2012). More so, when debt ratio is high, a company has to carry a bigger burden in the sense that principal and interest payments take a significant amount of the company's profit (Abdullah et al., 2016). This study expects a positive relationship between leverage and bankruptcy. Leverage is represented by total liabilities to total assets, long-term liabilities to total asset, current liabilities to total asset and current liabilities to total equity (refer to section 2.4.1 on review of profitability measures). Based on the foregoing, the study hypothesizes that:

H2: There is a positive relationship between leverage and bankruptcy.

3.4.1.3 Liquidity Ratios

Liquidity ratios are important for a company's financial health. Liquidity ratios are used to determine a company's ability to pay off its short-term debt obligations. The higher the value of the ratio, the larger the margin of safety that the company possesses to cover short-term debts. A company's ability to turn short-term assets into cash to cover debts is of the utmost importance when creditors are seeking payment. A company is solvent when it owns more than it owes; in other words, it has a positive net worth and a manageable debt load. A company with adequate liquidity have enough cash available to pay its bills and maintain its daily business needs. Liquidity crisis can happen when circumstances arise that make it difficult for a company to meet short-term obligations such as repaying their loans and paying their employees' salaries. As such management are faced with tough

decisions to reduce debt. Insolvency increases the risk of firms' ability to meet their financial commitments, which is likely to cause financial distress (Abdullah et al. 2016; Abdullah et al. 2014; Altman et al. 2010).

As a matter of precautionary measures, SMEs need to maintain sufficient level of liquidity in order to pay their bills and maintain its daily business needs. Insufficient liquidity would expose the firm to a greater uncertainties and exacerbate its financial situation and force it into bankruptcy. The higher the illiquidity, the higher the bankruptcy probability. Studies also find liquidity as one of the main determinants of bankruptcy for small businesses, given its significant effect on business sustainability (Arslan & Karan 2009; Chotima, 2013; Fidrmuc et al., 2006; Fidrmuc & Hainz 2010; Khorasgani, 2011; Lugovskaja, 2009; Monelos et al., 2011; Monelos et al., 2012; Moscalu 2012; Sirirattanaphonkun & Pattarathammas 2012). Thus, this study expects a negative relationship between liquidity ratios and bankruptcy.

H3: There is a negative relationship between liquidity and bankruptcy.

3.4.1.4 Activity Ratios

Activity ratios are key to analysing how effective and efficient a company is in managing its assets to produce sales. Companies in the manufacturing sector pays special attention to operational efficiency as this sector require large investments in facilities and equipment. Furthermore, companies strive to reduce production costs, improve processes in production and optimizes its asset efficiently in order to achieve operational excellence. Therefore, for the purpose of this study, asset turnover and expenses ratios are used as the activity ratios measures.

The asset turnover ratio is commonly used as a metric in manufacturing sector that make substantial purchases for facilities and equipment in order to drive up output. The asset turnover ratio indicates the amount of revenues, or sales, a company generates for each dollar of assets invested. In order for the company to be effective and efficient, those assets must be fully utilised to generate sales. The asset turnover ratio is an important asset management ratio because it helps companies to assess how efficient are they in using the companies' assets. A higher ratio is indicative of greater efficiency in managing asset, and how fast a company is able to generate sales through the use of its assets.

However, a low asset turnover ratio, may indicate that a company is inefficient in the use of its assets. Firms with low asset turnover ratios are expected to experience high probability of bankruptcy. Studies show that asset turnover is a significant predictor of bankruptcy among SMEs (Altman & Sabato, 2007; Edmister, 1972; Ferreira et al., 2014; Teti et al., 2012; Pederzoli & Torricelli, 2010). Thus, it is hypothesise as follows:

H4a: There is a negative relationship between activity ratio (asset turnover) and bankruptcy.

Furthermore, the expense ratio is also a measure of how efficient a company is. The ratio comprised of all non-production or operating costs of a business that are not included in the production cost which include for example salaries, commissions charged by agents to facilitate transactions, travel expenses for executives, advertising and marketing costs, rents and other utilities. Therefore, expense ratio should reflect to a significant extent managerial discretion in spending company

resources. An expense ratio that is increasing over time means that the company is operating less efficiently from period to period and indicate the inability of managers to control cost, whereas a low expense ratio indicates efficiency and the ability to control costs (Anderson et al., 2007). Firms with high expense ratios are expected to experience high probability of bankruptcy due to inability of the management to control cost that will trim the company's profit. Thus, it is hypothesise as follows:

H4b: There is a positive relationship between activity ratio (expense ratio) and bankruptcy.

3.4.1.5 Size

The size of a firm affects performance in many ways. Key features of a large firm are its diverse capabilities, large market share, the abilities to exploit economies of scale and scope, the formalization of procedures. These characteristics allow larger firms to generate better performance relative to smaller firms (Penrose, 1959). Large firms benefit from having better reputation as compare to small firm and it helps them to facilitate and attract customers and qualified managerial talent (Wiklund, Baker & Shepherd, 2010). Furthermore, the greater resource base of larger firms enables them to adjust better to economic downturns and respond more appropriately to adverse external events (Bumgardner et al., 2011). On the other hand, small size firms are more flexible and faster in making decisions due to the lack of excessive administrative processes. The flexibility of smaller size firms may enable them to cope with external changes (Penrose, 1995). However, they mostly concentrate on narrow market-niches, have resources constrained, difficulty in

hiring qualified employees and are more vulnerable to poor decision making which may lead to the risk of bankruptcy (Wiklund *et al.*, 2010).

The issue of firm size is important for a number of reasons in the context of SMEs. SMEs with larger size may have access to both retained earnings and external funds because the companies are seen as well established and have a lot of growth potentials. SMEs with larger size may also have better incentives in terms of getting a good interest rate and also a better discount rate due to a large quantity purchases from their suppliers compared to smaller firm. The studies that have examined bankruptcy and firm size have established that small size firms fail more often due to internal causes (e.g. operational management problems, inexperienced and incompetent management) while large firms fail mostly due to external causes (environment, competition, demand) (Hall & Young, 1991; Thornhill & Amit, 2003; Wiklund *et al.*, 2010). Similarly, Abdullah et al. (2016) and Altman, Haldeman and Narayanan (1977) highlights that smaller companies have a higher probability of bankruptcy. Based on the arguments put forward, the study hypothesizes that:

H5: There is a relationship between size of SME and bankruptcy.

3.4.2 Non-financial Indicators

From the review of literature two non-financial variables are selected namely, age of business and business location to be included in the analysis. These variables are chosen based on their popularity among the non-financial variables in the literature and their significance in predicating bankruptcy among SMEs.

3.4.2.1 Business Location

Strategic business location is critical to the success of any business. Business location has been widely recognized as an important factor in determining the success of an enterprise. Good business location may enable a struggling business to ultimately survive and thrive while a bad location could spell disaster to even the best-managed enterprises (Minai & Lucky, 2011). In developing countries (like Malaysia and Nigeria etc.), business location could make a lot of influence on business success or failure. This is because some states or cities in those countries would be much more developed compared to others in terms of infrastructure, access to finance, ease of doing business, business opportunities among other factors (Eickelpasch, Hirte & Stephan, 2015). This could be due to government supports and initiatives to develop the states as these states contribute significantly towards economic development of the country (Eickelpasch et al., 2015).

Businesses in more developed location can be viewed as an enabler of resource acquisition and capability development as it can provide competitive advantages such as access to proactive business networks which include having good rapport with customers, suppliers and industry and government associations which are more likely to be in close proximity (Westhead et al., 2004). Additionally, the business in this particular location will benefit from favourable supply side conditions, access to skilled labour, financial institutions and technology partners (Fuller-Love, Midmore & Thomas, 2006; Westhead et al., 2004). Financial institution such as commercial banks will consider business in developed states as having less risk and provide lower interest rate to the businesses having operations there as compare to the businesses in other states that are less developed. Furthermore, government

assistances are more reachable in developed states (Bennett & Smith, 2002). In support of this argument, Behr and Guttler (2007) find that regional factor is negative and a significant driver of SME's bankruptcy in Germany. The finding show that companies in eastern Germany are substantially riskier than their counterparts in western Germany because of eastern Germany firms are on average younger, have worse cost structures and operate in a more difficult economic environment (Behr & Guttler, 2007).

In Malaysia for example, Selangor, Kuala Lumpur, Johor, Sarawak and Pulau Pinang contributed 75.0 percent to the national growth (DOSM, 2014). The contribution to GDP¹⁴ at purchaser's prices accounts for 64.8 percent, with Selangor contributing the largest share (USD 52.69 million), followed by Kuala Lumpur (USD 34.48 million), Sarawak (USD 21.15 million), Johor (USD 20.42 million) and Pulau Pinang (USD 15.53 million) (DOSM, 2015). Despite the moderate economic growth between 2013 and 2014, Selangor contributes 29.7 percent to the manufacturing sector followed by Pulau Pinang with 13.6 percent, Johor with 12.6 percent and Sarawak with 10.3 percent, contributing a total of 66.2 percent (DOSM, 2014).

Therefore, it is reasonable to believe that SMEs in these states would be less prone to bankruptcy compared to SMEs in the other states as these states are more

¹⁴ GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.

For more detail, please refer to <https://datahelpdesk.worldbank.org/knowledgebase/articles/114947-what-is-the-difference-between-purchaser-prices-p> or <https://www.researchgate.net/post/Which-GDP-is-better-for-an-economic-analysis>

industrialised with good infrastructure, market potentials, and more vibrant economic environment and activities. Thus, for the purpose of this study, Selangor, Kuala Lumpur, Sarawak, Johor and Pulau Pinang out of the thirteen states in Malaysia are considered to be the more industrialised states or cities in Malaysia. SMEs in these states are expected to have more advantages and less likely to fall into bankruptcy compared to those SMEs in the less industrialised states.

Similarly in Nigeria, the performance and contribution of Lagos, Rivers, Delta, Kano and Abuja to national economic development are significant towards the government realization of target of Vision 2020 (SMEDAN, 2013). These states contributed 45.03 percent to the country's GDP in 2014, with Lagos contributing the largest share (USD 91.1 million), followed by Rivers (USD 21.1 million), Delta (USD 16.7 million), Kano (USD 12.4 million) and Abuja (USD 11.5 million) (Eniola, 2015; NBS, 2014; Service, 2016). Moreover, these states contributes 38.2 percent of the total established SMEs across the country, with Lagos accounting for the largest share of 16.01 percent followed by Kano (11.38%), Rivers (4.23%), Abuja (3.69%) and Delta (3.12%) (SMEDAN, 2013). The combined states (Lagos, Rivers, Delta, Kano and Abuja) accounts for 40 percent of the total employment by SMEs in the country (SMEDAN, 2013). Consequently, in view of their contribution and importance towards Nigerian economic development, SMEs in Lagos, Rivers, Delta, Kano and Abuja out of the thirty six states in Nigeriaaa would be less prone to bankruptcy compared with SMEs in other states.

On another perspective, SMEs located in more industrialised states are more likely to face competition from other SMEs as well as larger corporation and multinational

companies. Industrialised states attract more industry players, which makes the competition more intense in those areas (Phelps, Fallon, & Williams, 2001). Additionally, SMEs in these areas are more likely to incur more operating cost in terms of materials, labours and other operating overheads and would probably require more investments in net working capital (Watson & Everett, 1996). Therefore, the SMEs would require more financing which would probably come from the owner or from a third party, such as a bank. Then, it seems reasonable to suggest that businesses located in more industrialised states (with relatively higher competition, higher cost and higher capital needs) are more likely to fail when things go wrong. Therefore, based on this arguments, the study hypothesize that:

H6: There is a relationship between business location and bankruptcy.

3.4.2.2 Firm Age

Long established firms become more efficient over time. Firms discover what they are good at and learn how to do things better (Arrow, 1962; Jovanovic, 1982; Ericson & Pakes, 1995). They specialised and find ways to standardized, coordinate, and speed up their production processes, as well as to reduce costs and improve quality. Older firms are more experienced and are not prone to the liabilities of newness and can therefore enjoy superior performance (Stinchcombe, 1965). Additionally, older firms can be more profitable because of several strategic or operational advantages. Firms are able to tap into the relevant customer segment and provide differentiated products that meet demand which will subsequently help them in gaining customer loyalty and build up better rapport with suppliers (Majumdar, 1997). When firms become older, they become more transparent and are likely to gain access to cheaper debt financing given to the well-established

reputation and good relationship with creditors (Coadă, Segarra & Teruel, 2013), thus, older firm are less likely to bankruptcy.

Studies finds that age of SME is negatively related to bankruptcy. This hypothesis has been supported by a number of studies (Abdullah et al., 2014; Abdullah et al., 2016; Altman et al., 2010; Blanco et al., 2007; García-Posada & Mora-Sanguinetti, 2013; Shane, 1996). For example, Jovanovic (1982) argues that younger firms are more likely to fail because they face greater variability in their cost functions while they learn about their industry and management capabilities. Once a business has survived for the first few years the chances of failing are significantly reduced. Jovanovic (1982) supports that the longer a company has existed, the higher the chance of it to survive as a result of its ability to learn and gained more experience as well as having management capabilities. In contrast, a younger SME is likely to fail compared to an older SMEs due to lack of experience in the business environment and growth development potentials. Plattner (2002) argues that SMEs tend to fall into insolvency than large corporation because they are usually less diversified and are more likely to face financing restrictions. Based on the arguments, this study argues that:

H7: There is a negative relationship between age of SME and bankruptcy.

3.4.3 Governance Indicators

As mentioned earlier, corporate information of privately held companies is difficult to assess or in some cases is not available compared to public listed companies. Based on the available information at our disposal, the study examine the effect of controlling shareholder, number of directors, proportion of independent directors,

duality of managing director (MD), gender and ethnicity of MD on bankruptcy. They are selected based on their popularity in the SMEs literature while the ethnicity of MD is selected based on the characteristics of SMEs set-up. Ethnic diversity has gained attention in the academic literature as it is seen as one of the ways in enhancing governance in the board (Certo, Richard & Dalton 2006; Roberson & Park, 2007). Board diversity is argued to enhance effective decision making and better utilisation of the talent pool (Certo et al., 2006; Roberson & Park, 2007).

Corporate governance aims at the protection of stakeholders. It is used as a mechanism to reduce agency problems (Shleifer & Vishny, 1997). Effective corporate governance systems are of significant importance not only in large firms but also in SMEs (Shleifer & Vishny, 1997). Good governance will benefit both the company and the economy in general. When the interests of contracting parties deviate from the shareholders, control mechanisms are necessary to mitigate agency problems (Agrawal & Knoeber, 1996). Monitoring and controlling mechanisms by outside parties include auditing, formal control systems, budget restrictions, and the establishment of incentive compensation systems (Jensen & Meckling, 1976). Other mechanisms to mitigate agency problems are board structure, the use of independent board members on the board, and monitoring by the firm's own large shareholders (Agrawal & Knoeber, 1996).

3.4.3.1 CEO Duality

Advocates of agency theory argue that the positions of CEO and chairman should be separated. They argued that a single officer who holds both positions creates a

conflict of interest that could negatively affect the interests of the shareholders. Moreover, they argued the interests of the owners will be sacrificed to a degree in favour of the management, that is, there will be managerial opportunism (Donaldson & Davis, 1991; Eisenhardt, 1989; Fama & Jensen, 1983; Jensen & Meckling 1976; Roe, 2004; Williamson, 1985). In support of their arguments, studies find that CEO-duality has a positive correlation with company bankruptcy. CEO-duality leads to more controlling because the decision making is centred to one individual (Argenti, 1986; Daily & Dalton, 1994; Hambrick & D'Aveni, 1992; Mallette & Fowler, 1992).

However, Ciampi (2015) finds that CEO-duality is negatively correlated with SMEs bankruptcy. This finding supports the stewardship theory. Accordingly, CEO is not an opportunistic shirker, but wants to do a good job by becoming a good steward of the corporate assets. When one person holds both roles, he or she is able to act more efficiently and effectively. Holding dual roles as CEO/chairman creates unity across the company's managers and board of directors, which ultimately allows the CEO to serve the shareholders better (Davis et al., 1997; Kim, Al-Shammari, Kim, & Lee, 2009). Thus, the presence of CEO-duality as advocate by stewardship theory would enhance the effectiveness and productivity of the board thereby achieving superior returns to shareholders rather than taking a separation of the roles of chair and CEO (Donaldson 1985; Donaldson & Davis, 1991). Therefore, based on the argument put forward, the study hypothesise that:

H8: There is a relationship between CEO duality and bankruptcy.

3.4.3.2 Board size

Board size is the number of directors on the board. Finding the right board size that affects the capacity of companies to function efficiently and effectively has been a matter of continuing debate (Dalton, Daily, Johnson & Ellstrand, 1999; Hermalin & Weisbach, 2003; Yermack, 1996). The number of directors in a company's board is proved to be a significant indicator of SMEs' bankruptcy. Larger board can decrease the probability of SMEs bankruptcy (Abdullah et al., 2016; Keasey & Watson, 1987). Chaganti et al. (1985) find that a larger boards assist in firm survival. Large board size is associated with having quality advice and counsel to the CEO (Dalton et al 1999). Moreover, a company with a large board would have access to diverse skills, expertise and experience from different members to help counsel the CEO effectively on investment opportunities and business improvement (Eisenberg, Sundgren, & Wells, 1998). Having a large board size also enable companies to have access to more resources and information that would assist the management in formulating strategies (Lehn, Sukesh, & Zhao, 2004).

Conversely, some literature find that board size has a positive correlation with the probability of bankruptcy (Chaganti et al., 1985; Ciampi, 2015; Yermack, 1996). A large number of directors on board is difficult to coordinate. Some directors may not contribute and may tag along as free-riders which reduce the efficiency of the board. A large board could also result in less meaningful discussion, since expressing opinions within a large group is generally time consuming and difficult (Dalton et al., 1999; Lipton & Lorch, 1992). Instead, Jensen (1993) recommended a small board because of efficiency in decision making due to greater coordination and lesser communication problems. A smaller board of directors is more effective in

monitoring and controlling activities as strategic decisions could be made faster (Certo, Richards, & Dalton, 2006). In support of the arguments, smaller boards are found to enhance firm's performance (Eisenberg et al., 1998; Yermack, 1996). Therefore, it is hypothesised that:

H9: There is a relationship between board size and bankruptcy.

3.4.3.3 Controlling Shareholder

According to advocates of agency theory, high degree of ownership concentration creates positive effects on firm performance as controlling shareholders or large shareholders often have the capability to effectively observe and monitor managers (Jensen & Meckling, 1976; Shleifer & Vishny, 1986). However, when ownership concentration exceeds a certain level, controlling shareholders tend to exercise their rights for private benefits at the expense of minority shareholders (Shleifer & Vishny, 1997). For example in emerging markets where there is lack of legal protection, minority shareholders may face expropriation risks from controlling shareholders (Ishak & Napier, 2006; La Porta, Lopez-de-Silanes, & Shleifer, 1999). The types of expropriation include a transfer of below-market value asset to the controlling shareholders, corporate expenditures on non-value creating assets and corporate diversification plans that benefit the portfolio of controlling shareholders (Su, Xu, & Phan, 2008). In support to the above argument, Abdullah et al. (2016) find controlling shareholder is positively related to the bankruptcy of SMEs in Malaysia.

However, Ciampi (2015) find that controlling shareholder is negatively related to SMEs' bankruptcy. Controlling shareholders of small firms tends to recognise their

personal success with the company's success. Accordingly, controlling shareholders would be motivated to do their best for the firm as a whole. This is because they are emotionally involved with the company and their personal reputation is in most cases closely tied to the longevity and the success of the business (Ciampi, 2015). As such having controlling shareholder leads to stability, lower conflict among stakeholders, and is a key element to realizing a broad convergence of interest between the different stakeholders (Ciampi, 2015). Thus, based on the arguments, it is hypothesized that:

H10: There is a relationship between controlling shareholder and bankruptcy.

3.4.3.4 Independent Director

Independent directors can potentially assist the company during crisis because the company can have access to useful resources and information and can improve relationships with the external environment facilitate by outside directors (Dowell et al., 2011; Pfeffer & Salancik, 1978). The presence of independent directors would benefit the company to have a better access to external resources and management competencies as in some cases there is a possibility for the independent directors to replace the managers when necessary (Hillman & Dalziel, 2003; Weisbach, 1988).

Independent directors are supposed to be guardians of the shareholders' interests through monitoring. Empirical evidence shows that independent directors are effective monitors and disciplining tool to align manager's interest with the shareholders (Coughlan & Schmidt, 1985; Hermalin & Weisbach, 1988). Independent directors can reduce agency problem among stakeholders and may contribute to the value of firms through their evaluation of strategic decisions

(Brickley & James, 1987; Byrd & Hickman, 1992; Lee et al., 2005) and dismissal of inefficient and poorly performing management (Weisbach, 1988). Additionally, Ciampi (2015) finds that independent directors significantly reduced the probability of bankruptcy among SMEs in Italy. The presence of independent directors can help SMEs to form a system of check and balance designed to improve monitoring activities that could benefit the firm's owner (Ciampi, 2015). Consequently, this leads to the following hypothesis:

H11: There is a negative relationship between board independent and bankruptcy.

3.4.3.5 Gender of Managing Director

Board diversity suggests that boards should reflect the structure of the society and appropriately represent the gender, ethnicity and professional backgrounds. Boards are concerned with having the right composition to provide diverse perspectives (Milliken & Martins, 1996; Biggins, 1999). Gender of CEO is part of the wider concept of board diversity (Milliken and Martins, 1996). Hillman et al. (2002) argued that women CEOs are far more likely to hold valuable, unique and rare information to provide different perspective during board discussion because of their non-corporate background. He believed that women usually face glass ceiling in the corporate sector and majority of them end up in the public sector (Hillman et al., 2002). Studies have shown that women CEO would benefit the firm governance and performance through an influx of different skills, abilities, fresh perspectives and weaving of new dynamics to board deliberations (Jamali et al., 2007; Fondas & Salsalos, 2000). Accordingly, women CEOs are found to be younger as compare to their male counterparts and therefore the firm would benefit from infusion of new ideas and tactics to discussions (Bilimoria & Wheeler, 2000). Women also vary in

their views, values and ways to express their opinions. This would possibly result in their questioning of the conventional wisdom and more open discussions (Huse & Solberg, 2006). Such diverse view points by women directors will incite lively boardroom discussions, thereby enhancing the quality of decision making (Letendre, 2004).

For example, SMEs led by women CEO tend to have a higher sale and profitability growth than SMEs led by male counterpart (Davis et al., 2010; Singhathep & Pholphirul, 2015). In a commercial context, women CEOs place greater emphasis on market orientation as women make majority of sales especially in consumer goods and media industries and therefore, can bring perspectives on women's products/market issues (Burke, 2003). Furthermore, Abdullah et al. (2016) in their study on bankruptcy among SMEs in Malaysia, they find that gender of managing director (MD) is significant and positively related to corporate bankruptcy. The results show that men managing directors are more likely associated to bankruptcy among SMEs than the female counterpart. Women are believed to be more concerned with ethical behaviour than men in the work place (Ford & Richardson, 1994). Women MD worry more about the way the company money is spent and normally extract less personal benefits from the company than men counterpart (Bart & Bontis, 2003; Bliss & Potter, 2002). Furthermore, female MD will make more conservative decisions than men, and therefore, female MD are more risk averse than men and as such their firm risk level will be smaller than firms managed by male MD (Vandergrift & Brown, 2005; Wei, 2007).

On the other hand, some studies find the performance of male CEO is better than that of the female CEO. Female CEOs are having higher rate of bankruptcy as compare to their male counterpart (Fairlie & Robb, 2009; Robb, 2008). This is because female CEOs are more often outsiders and are vulnerable. They have little knowledge about the organisation and cannot diagnose the problems quickly and lack the understanding of the organisational culture (Fairlie & Robb, 2009; Robb, 2008). Long-term growth of an organisation depends on industry and firm-specific knowledge. Female CEO also faced difficulties in relation to family responsibilities (in particular responsibility for childcare) (Mirchandani, 1999) which is consider a major constrain. Furthermore, female CEOs are more risk averse in terms of investment and financing decisions (Vandergrift & Brown, 2005; Wei, 2007). Firms run by female CEOs will make less risky corporate choices and experience less volatile outcomes. Their avoidance of risky projects with positive expected net present values will reduce the efficiency of the capital allocation process. Thus, female CEOs do not appear to allocate capital efficiently (Faccio, Marchicab & Mura, 2016; Hsu et al., 2013). More so, due to lack of industry experience, women CEO concentrate on less profitable projects (Alowaihan, 2004; Loscocco et al., 1991) and as such create a barrier to business (Fischer et al., 1993). Thus, the study hypothesised that:

H12: There is a relationship between gender of managing director and bankruptcy.

3.4.3.6 Ethnicity of Managing Director

Hofstede (1991) suggest that the two main ethnic groups in Malaysia, the Malays and the Chinese are both low on masculinity but high on power distance. The Malays have high uncertainty avoidance which is reflected by their uneasiness in

dealing with ambiguities and uncertainties. This shows that the Malay are more likely to be risk averse in doing business and their firms are likely to have lower risk compared to others races. However, with the current competitive business environment, the firms might also be losing out on business opportunities that could help their firms to grow in the future. Additionally, the Malays encourage collectivism. This in turn would potentially improve the relationship between manager and employees in an organisation. A high level of collectivism may indicate that the persons could communicate easily with their subordinates because of their readiness to cooperate (Triandis, 1993). When CEOs encourage collectivism in their firms, there would be an optimal communication between leaders and followers. The followers receive greater support, encouragement and consideration on achieving the mission and fulfilling their responsibilities (Graen & Scandura, 1987). This would potentially improve firm's performance and reduce the possibility of default.

In contrast, the Chinese are willing to accept new challenges and to take a greater risk (Haniffa & Cooke, 2000). SMEs managed by the Chinese would probably take up more risk and as a result enjoy high return from their investments compared to other firms. Furthermore, the Chinese are more individualistic (Haniffa & Cooke, 2000). Individualism results in higher innovation (Gorodnichenko & Roland, 2011). As a result, firms managed by the Chinese are likely to have a higher innovation rate which would lead to higher levels of productivity and output in the long run (Gorodnichenko & Roland, 2011). Therefore, in line with the arguments put forward, the study hypothesised that:

H13: There is a relationship between ethnicity of managing director and bankruptcy.

3.4.4 Macroeconomic Indicators

At the macro level, the issue of bankruptcy has significant consequences to financial stability and economic growth. Given the potential severity of economic and social consequences of bankruptcies, factors that drive the business sector vulnerability to bankruptcy and insolvency are important for forward-looking strategies or policies of banks, policymakers and other stakeholders. An investigation into financial, non-financial and governance data alone may present an incomplete image of the relations underlying the bankruptcy process. This is because aggregate economy risk arising from the uncertainty of business and credit cycles and other macroeconomic influences, may affect the volatility of cash flows and the risk of bankruptcy. Hence, to achieve a more robust model of bankruptcy, macroeconomic variables should be incorporated. Given the scope of this research on SMEs and the broad macroeconomic indicators, the study decided to narrow the research on the effects of some critical macroeconomic indicators such as GDP growth, unemployment rate, interest and inflation rate. The selection is also based on their popularity in the literature of SMEs.

3.4.4.1 Gross Domestic Product

GDP refers to the market value of all final goods and services produced within a country in a given period. It is often measured as an indicator of a country's standard of living. It represents the total economic activity of a specific country by totalling the value of its production, the income earned from the production or a series of

more complex assessments. The GDP growth rate is an indicator of economic growth. A positive GDP growth is an increase in the capacity of an economy to produce goods and services, compared from one period to another. GDP growth creates a positive impact on the confidence of businesses, as their profits would gradually increase with economic growth, due to high spending from consumers (Mačerinskienė & Mendelsonas, 2013). This also means more demand for businesses' goods and services which will result in higher profitability and survival.

However, a negative growth in GDP is often associated with economic depression and economic recession. It indicates that consumers cut back their spending, and the economy slows down. Slowing demand leads companies to lower profitability and employee lay off, which further affects consumer confidence and demand. GDP is found to be significant and negatively related to bankruptcy (Ahmad et al., 2008; Aneta & Anna 2014). The finding shows that the higher the GDP, the lower the risk of bankruptcy because a higher GDP indicates economic growth in the country which will result in a higher profitability for firms with the assumption of *ceteris paribus*, which in turn lowers the rate of bankruptcies. Mačerinskienė and Mendelsonas (2013) describe how various macroeconomic variables influenced the number of bankruptcies in Lithuania. The finding shows that the growth rate of GDP is the major factor that significantly predicts bankruptcy. Moreover, growth in GDP creates better investment opportunities for firms and also increases corporate liquidity which subsequently reduces bankruptcy. Therefore, GDP is expected to be having a negative relationship with bankruptcy and the following hypothesis was formulated:

H14: There is a negative relationship between growth in GDP and bankruptcy.

3.4.4.2 Unemployment Rate

Unemployment rate measures the percentage of unemployed people in a country's workforce. High unemployment rate generally indicates an underperforming economy or a falling gross domestic product. As fewer people have jobs, businesses would not be able to produce as many goods and services. As a result, the output of goods and services in the economy (GDP) will be lower. This also has an impact on government spending and will negatively affect finances. Furthermore, lower consumer spending will be experienced with high unemployment rate because consumers have less money to spend on goods and services when they are out of job (Everett & Watson, 1998). Therefore, it weakens consumers' purchasing power which is the driver of local economies. As a result, businesses will experience lower sales revenue and will likely see a fall in profits.

Everett and Watson (1998) explore the impact of macroeconomic factors on small bankruptcy. The results suggests that unemployment rate is positively associated with bankruptcy of small businesses in Australia. The finding of Everett and Watson (1998) is consistent with Hudson (1989) and Millington (1994) where they reported a significant positive relationship between unemployment rate and bankruptcies. This is because higher levels of unemployment may indicate that the economy is not growing which will subsequently reduce consumer spending and, therefore, a reduction in business revenue. Thus, the study hypothesised that:

H15: There is a positive relationship between unemployment and bankruptcy.

3.4.4.3 Inflation Rate

Many economists maintain that inflation at certain levels is needed to drive consumption, in order to have higher levels of spending which are important for economic growth (Keynes, 2008; Markwell, 2006; O'Sullivan & Sheffrin, 2003). Inflation is usually target by governments around the globe, believing that a gradual increase of price level keeps businesses profitable (Keynes, 2008; Markwell, 2006; O'Sullivan & Sheffrin, 2003). Additionally, when the economy is not running at capacity, meaning there is unused labour or resources, inflation theoretically helps increase production. More dollars translate to more spending, which equates to more aggregated demand. More demand, in turn, triggers more production to meet that demand. However, if aggregate demand in the economy fell, the resulting weakness in production and jobs would precipitate a decline in prices and wages (Keynes, 2008; Markwell, 2006).

However, as the economy booms and approaches the limits of productivity at a point in time, manufacturing businesses would typically feel higher sales prices and higher costs and higher interest rates. With higher interest rates, firms may find it difficult in raising external financing and therefore might face cash shortages to support their working capital and long term projects (Whited, 1992). Furthermore, valuable investment opportunities may be missed by businesses due to high cost of borrowing as a result of high inflation (Stiglitz & Weiss, 1981). Moreover, inflation can make an economy and businesses uncompetitive. Businesses would find it difficult to compete in the market especially from foreign competition due to higher prices and higher cost of production and debt-servicing and hence reducing the company's profits and cash flows (Bhattacharjee, Higson, Holly & Kattuman,

2002). Studies have shown that high level of inflation is associated with bankruptcy (Bhattacharjee et al., 2002, Millington, 1994; Wadhwani, 1986). Changes in the level of inflation can affect the volatility of cash flows and reduce the firm's ability to pay interests on its debt, thus increasing the risk of financial distress.

When inflation is high, prices need to be raised and this infuriates consumers who blame producers for increasing prices. Small businesses with their limited market share and capacity will try to keep from raising prices in fear of losing major customers to competitors. This squeezes profit margins and can cause companies to produce products that sell for less in real terms than they cost to produce. This would lead to bankruptcy in the short or long run. Based on the arguments put forward, the study hypothesizes that:

H16: There is a relationship between inflation rate and bankruptcy.

3.4.4.4 Interest Rate

Changes in interest rates can help businesses or hold them back. Companies pay interest on money they borrow, and when they have extra cash, they receive interest from a safe investment. Majority of small businesses carry relatively a high amount of debt that are sensitive to changes in the cost of carrying the debt (Hall & Young, 1991). A high interest rate makes it more expensive for companies to borrow funds to finance their operations, payroll and purchases (Michael & William, 2013). This means with a high interest rate, businesses use more of their earnings to pay interest on their loans, thereby decreasing their profits. Furthermore, some businesses may decide not to start new projects or expand their business operations during periods of high interest rates and therefore, affects the growth potentials of the company

(Michael & William, 2013). In support of the above arguments, a high interest rate is considered as the reason for the bankruptcy of small businesses in a survey conducted by Hall and Young (1991) and Peterson, Kozmetsky, and Ridgway (1983).

Hudson (1989), Millington (1994), Salman, Fuchs and Zampatti, (2015), Wadhvani (1986) and Young (1995) report a significant positive relationship between interest rates and bankruptcy. They find that, bankruptcy may be induced by raising borrowing costs in excess of profit margins of businesses. Accordingly, in times of high interest rates, consumer discretionary income is reduced which impacts the revenues of many small businesses. Companies that have to pay higher interest for their loans tend to pass on the added expense by charging more for products and services. As a result, consumers often cut back their purchases due to the higher prices charge by the companies. Consistent with the finding, previous studies have empirically shown that interest rate has a significant influence on the number of bankruptcy (Cuthbertson & Hudson, 1996; Vlieghe, 2001; Liu, 2004). Thus, the study hypothesised that:

H17: There is a positive relationship between lending rate and bankruptcy.

3.5 Method

In line with the literature review, logistic regression and artificial neural network methods are used for the analysis in this study. The motive is to predict bankruptcy among SMEs in Malaysia and Nigeria using financial, non-financial, corporate governance and macroeconomic indicators. Classification accuracy rate of each

method is compared in order to identify the method that provides a higher predictive accuracy rate. Below are the estimated equations for each method;

3.5.1 Logistic Regression

Binary logistic regression deals with situations in which the observed outcome for a dependent variable can have only two possible outcome. In the case of this study a bankrupt SME is coded as “1” while non-bankrupt SME is coded as "0". Logistic regression is used to predict the odds of being a case based on the independent variables. The odds are defined as the probability that a particular outcome is a case divided by the probability that it is a non-case. Unlike ordinary linear regression, however, logistic regression is used for predicting binary dependent variables rather than a continuous outcome. Given this difference, the assumptions of linear regression such as linearity, normality, conditional mean, conditional correction, rank and homoscedasticity, which relates to the distribution of explanatory variables in linear regression are not required in the non-linear models (Hair et al., 2010; Hosmer & Lemeshow, 2000).

However, logistic regression has its own assumptions that need to be met. First of all, it does not assume a linear relationship between the dependent and independent variables. It can handle any sorts of relationships, because it applies a non-linear log transformation to the predicted odds ratio. Secondly, the independent variables need not be interval, nor normally distributed, nor linearly related, nor of equal variance within each group. Thirdly, logistic regression can handle ordinal and nominal data as independent variables. The independent variables do not need to be metric (interval or ratio scaled) (Hair et al., 2010).

Logistic regression is estimated using the maximum likelihood method. The nonlinear nature of the logistic transformation requires the maximum likelihood procedure to be used in an iterative manner to find the most likely estimates for the coefficients (Hair et al., 2010). Logistic regression maximized the likelihood that an event would occur. The logit prediction model used in this study is as follows:

$$Z_i = \beta'x_i + u_i \quad (1)$$

Where:

Z_i = bankrupt if $Z_i > 0$; non-bankrupt otherwise.

x_i = EBIT, ROE, TLA, LTA, CLA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC, CONT, IND, NDIR, GENDER, MDD, MDEH, GDP, EMPY, LNR, CPI.

u_i = error term

Z_i ranges from $-\alpha$ to $+\alpha$

The probability and likelihood function for the bankrupt firm can be defined as follows:

$$P_i = E(Y = 1 / x_i) = \frac{1}{1 + e^{-(\beta'x_i + u_i)}} \quad (2)$$

Logistic distribution function is represented in equation (2). If P_i represents the probability of bankrupt as given in the equation (2), then $(1-P_i)$ would be the probability of non-bankrupt.

$$1 - P_i = \frac{1}{1 + e^{Z_i}} \quad (3)$$

A company is classified as bankrupt if the calculated probability from the logit model is more than 0.5, otherwise as non-bankrupt.

The binary logistic regression models for this study includes model 1 (employs only the financial and non-financial variables) which is the benchmark model used to compare the results obtain from models 2 and 3. This is because most of the studies on SMEs have been examining the influence of financial and non-financial variables to predict bankruptcy. Hence, model 1 acts as the benchmark model to see whether or not by adding corporate governance and macroeconomic variables in model 2, the accuracy of the rate of the bankruptcy prediction model could be improved. Model 3 incorporates financial, non-financial, governance and macroeconomic indicators to test the improvement of the predictive ability when these four categories of predictors are included. For each model, the study predicts the bankruptcy for three years prior to bankruptcy, two years prior to bankruptcy and one year prior to bankruptcy.

Furthermore, the enter method was chosen over the stepwise method in the analysis as it gives better predictive ability and better model fit (Memic, 2015). Stepwise regression requires that model selection is conducted through parameter inference (i.e. testing whether parameters are significantly different from zero) (Chatfield 1995), which can lead to biases in parameters, over-fitting and incorrect significant tests. The problem is that the algorithm used (forward selection, backward elimination or stepwise), the order of parameter entry (or deletion), and the number of candidate parameters, can all affect the selected model (e.g. Derksen & Keselman, 1992). This problem is particularly acute where the predictors are correlated. In addition, the number of candidate parameters has a positive effect on the number of nuisance (or noise) variables that are represented in the selected model (Derksen & Keselman 1992).

Stepwise regression procedures aim at identifying a single “best” model as the sole product of analysis. This can suggest a level of confidence in the final model that is not justified by the data, focusing all further analysis and reporting on that single model. Although one model may be selected, other models may have a similarly good fit and it is highly likely that there will be uncertainty surrounding estimates of parameters and which parameters should be included. The use of a single model as an inference may be misleading because there might be other models that could also fit the data. Therefore, this study used the enter method where all independent variables are entered into the equation at the same time. Each predictor is assessed as though it was entered after all the other independent variables were entered, and assessed by what it offers to the prediction of the dependent variable, that is different from the predictions offered by the other variables entering into the model.

Model 1:

$$Z_i = \alpha_0 + \beta_1 EBIT_{i,t} + \beta_2 ROE_{i,t} + \beta_3 TLA_{i,t} + \beta_4 LTA_{i,t} + \beta_5 CLA_{i,t} + \beta_6 CLE_{i,t} + \beta_7 LQT_{i,t} + \beta_8 WCT_{i,t} + \beta_9 NWC_{i,t} + \beta_{10} AST_{i,t} + \beta_{11} EXP_{i,t} + \beta_{12} LogTA_{i,t} + \beta_{13} LogCAP_{i,t} + \beta_{14} AGE_{i,t} + \beta_{15} BLC_{i,t} + \mu_t \quad (4)$$

Model 2

$$Z_i = \alpha_0 + \beta_1 CONT_{i,t} + \beta_2 IND_{i,t} + \beta_3 NDIR_{i,t} + \beta_4 GENDER_{i,t} + \beta_5 MDD_{i,t} + \beta_6 MDEH_{i,t} + \beta_7 GDP_t + \beta_8 EMPY_t + \beta_9 LNR_t + \beta_{10} CPI_t + \mu_t \quad (5)$$

Model 3¹⁵

$$\begin{aligned} Z_i = & \alpha_0 + \beta_1 \text{EBIT}_{i,t} + \beta_2 \text{ROE}_{i,t} + \beta_3 \text{TLA}_{i,t} + \beta_4 \text{LTA}_{i,t} + \beta_5 \text{CLA}_{i,t} + \beta_6 \text{CLE}_{i,t} + \beta_7 \text{LQT}_{i,t} \\ & + \beta_8 \text{WCT}_{i,t} + \beta_9 \text{NWC}_{i,t} + \beta_{10} \text{AST}_{i,t} + \beta_{11} \text{EXP}_{i,t} + \beta_{12} \text{LogTA}_{i,t} + \beta_{13} \text{LogCAP}_{i,t} + \\ & \beta_{14} \text{AGE}_{i,t} + \beta_{15} \text{BLC}_{i,t} + \beta_{16} \text{CONT}_{i,t} + \beta_{17} \text{IND}_{i,t} + \beta_{18} \text{NDIR}_{i,t} + \beta_{19} \text{GENDER}_{i,t} + \\ & \beta_{20} \text{MDD}_{i,t} + \beta_{21} \text{MDEH}_{i,t} + \beta_{22} \text{GDP}_t + \beta_{23} \text{EMPY}_t + \beta_{24} \text{LNR}_t + \beta_{25} \text{CPI}_t + \mu_t \quad (6) \end{aligned}$$

Where i refers to firm, t refers to time, and Z_i is a binary variable that equals to 1 for bankrupt SME, zero otherwise (non-bankrupt SME). EBIT is the ratio of earnings before interest and tax to total asset; ROE is the ratio of net income to share capital; TLA is the ratio of total liabilities to total assets; LTA is the ratio of long term liabilities to total assets; CTA is the ratio of current liabilities to total assets; CLE is the ratio of current liabilities to share capital; LQT is the ratio of current assets to current liabilities; WCT is the ratio of working capital to total liabilities; NWC is current assets minus current liabilities; AST is the ratio of sales to total asset; EXP is the ratio of selling, general and administrative expenses to total sales; LogTA is the logarithm of total assets; LogCAP is the logarithm of share capital; AGE is years of SMEs business operations and BLC is a dummy for business location that equal to 1 if the firm business location is in industrialised states, otherwise zero. CONT is a dummy for controlling shareholder that equal to 1 if a shareholder owns 33 percent or more of the company's outstanding shares and zero otherwise; IND is the proportion of independent directors on the board at the year-end; NDIR is the number of directors in the board; GENDER is a dummy where if the managing

¹⁵ The study use model 3 to test the research hypotheses as it combines financial, non-financial, corporate governance and macroeconomic indicators in a single model. Furthermore, model 3 is also use to test the improvement of the predictive ability when these four categories of predictors are included.

director is a male, it would equal to 1 otherwise zero; MDD is a dummy that equals 1 if the managing director is also the chairman, otherwise zero; MDEH¹⁶ is a dummy for ethnicity of managing director; GDP is the yearly percentage change in GDP; EMPY is the yearly percentage change in unemployment rate; CPI is the yearly percentage change in the consumer price index; and LNR is the yearly percentage change in lending rate.

3.5.2 Artificial Neural Network

The basic structure of Artificial Neural Network (ANN) consists of artificial neurons similar to biological neurons in the human brain that are grouped into layers. ANN functions consist of multiple processing units, where the input of one can serve as an output of another processing unit. Within a processing unit, the inputs are assigned with weights and summed up to form an activation value which is then passed to the output function of the unit and converted to an output. While the input converts into output within a processing unit, a pattern is recognize and stored, or 'learned' and can be recalled. The model works on a learning algorithm, whereby the weights are allocated and rated for the inputs/outputs /interconnections of processing units (Yegnanarayana, 2006).

¹⁶ Since the qualitative variable "MDEH" has four categories, in our analysis we can only introduce three dummies in order to avoid dummy trap. For example in the case of Nigerian sample, the following dummies were introduced:

HAUSA_{*i,t*} = 1 if the managing director is Hausa, 0 otherwise non-Hausa
 YAROA_{*i,t*} = 1 if the managing director is Yaroba, 0 otherwise non-Yaroba
 IGBO_{*i,t*} = 1 if the managing director is Igbo, 0 otherwise non-Igbo

In the case of Malaysian sample, the following dummies were introduced:
 MALAY_{*i,t*} = 1 if the managing director is Malay, 0 otherwise non-Malay
 CHINESE_{*i,t*} = 1 if the managing director is Chinese, 0 otherwise non-Chinese
 INDIAN_{*i,t*} = 1 if the managing director is Indian, 0 otherwise non-Indian

For prediction purpose, this study proposes the popular Multilayer Perceptron (MLP). MLP is a feed-forward network composed of an input layer, one or more hidden layers and an output layer (Zhang et al., 1999). The three-layer MLP is a commonly used ANN structure for two-group classification problems like the bankruptcy prediction (Charitou et al., 2004). The MLP layout can be diagrammatically presented as follows:

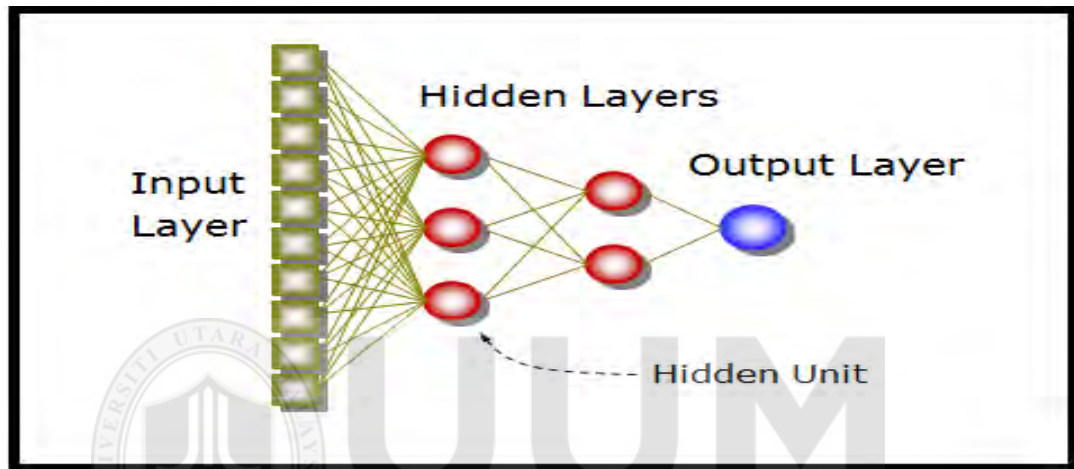


Figure 3.2
Multilayer Perceptron (MLP)

Multilayer perceptron model can be mathematically presented as (Zhang, Hu, Patuwo, & Indro, 1999):

$$y = f_2 (w_2 f_1 (w_1 x + b)) \quad (7)$$

Where y is the output from the network, $x = (x_1; x_2; \dots; x_n)$ is an input-vector of predictive or attribute variables, b is a bias, w_1 and w_2 are the matrices of linking weights from input to hidden layer and from hidden to output layer, respectively. f_1 and f_2 are the transfer functions for hidden node and output node, respectively.

The most popular choice for f_1 and f_2 is the sigmoid function. Sigmoid function such as the logistic function also has an easily calculated derivative, which can be important when calculating the weight updates in the network. Sigmoid functions are often used in artificial neural networks to introduce non-linearity in the model. A neural network element computes a linear combination of its input signals, and applies a sigmoid function to the result. A reason for its popularity is because the sigmoid function satisfies the property between the derivative and itself such that it is computationally easy to perform.

$$y = f(x) = \frac{1}{(1 + e^{-x})} \quad (8)$$

Sigmoid non-linearity takes a real valued number and “squashes” it into range between 0 and 1. f is the output of the i th node (neuron) and x is the weighted sum of the input synapses.

The purpose of network training is to estimate the weight matrices in Eq. (7) in a way that an overall error measure such as the mean squared errors (MSE) or sum of squared errors (SSE) is minimized. MSE can be defined as

$$\text{MSE} = \frac{1}{N} \sum_{j=1}^N (a_j - y_j)^2 \quad (9)$$

where a_j and y_j represent the target value and the actual network output for the j th training pattern respectively, and N is the number of training patterns.

Thus, the MLP models for this study are as follows:

Model 1

$$y = f_2 (w_2 f_1 (w_1 \text{EBIT}_{i,t} + w_2 \text{ROE}_{i,t} + w_3 \text{TLA}_{i,t} + w_4 \text{LTA}_{i,t} + w_5 \text{CLA}_{i,t} + w_6 \text{CLE}_{i,t} + w_7 \text{LQT}_{i,t} + w_8 \text{WCT}_{i,t} + w_9 \text{NWC}_{i,t} + w_{10} \text{AST}_{i,t} + w_{11} \text{EXP}_{i,t} + w_{12} \text{LogTA}_{i,t} + w_{13} \text{LogCAP}_{i,t} + w_{14} \text{AGE}_{i,t} + w_{15} \text{BLC}_{i,t} + b)) \quad (10)$$

Model 2

$$y = f_2 (w_2 f_1 (w_1 \text{CONT}_{i,t} + w_2 \text{IND}_{i,t} + w_3 \text{NDIR}_{i,t} + w_4 \text{GENDER}_{i,t} + w_5 \text{MDD}_{i,t} + w_6 \text{MDEH}_{i,t} + w_7 \text{GDP}_t + w_8 \text{EMPY}_t + w_9 \text{LNR}_t + w_{10} \text{CPI}_t + b)) \quad (11)$$

Model 3

$$y = f_2 (w_2 f_1 (w_1 \text{EBIT}_{i,t} + w_2 \text{ROE}_{i,t} + w_3 \text{TLA}_{i,t} + w_4 \text{LTA}_{i,t} + w_5 \text{CLA}_{i,t} + w_6 \text{CLE}_{i,t} + w_7 \text{LQT}_{i,t} + w_8 \text{WCT}_{i,t} + w_9 \text{NWC}_{i,t} + w_{10} \text{AST}_{i,t} + w_{11} \text{EXP}_{i,t} + w_{12} \text{LogTA}_{i,t} + w_{13} \text{LogCAP}_{i,t} + w_{14} \text{AGE}_{i,t} + w_{15} \text{BLC}_{i,t} + w_{16} \text{CONT}_{i,t} + w_{17} \text{IND}_{i,t} + w_{18} \text{NDIR}_{i,t} + w_{19} \text{GENDER}_{i,t} + w_{20} \text{MDD}_{i,t} + w_{21} \text{MDEH}_{i,t} + w_{22} \text{GDP}_t + w_{23} \text{EMPY}_t + w_{24} \text{LNR}_t + w_{25} \text{CPI}_t + b)) \quad (12)$$

where y is the output from the network. The explanatory variables are the same as those defined in the logistic regression model. $x = (x_1; x_2; \dots; x_n)$ is an input-vector of predictive or attribute variables, b is a bias, w_1 and w_2 are the matrices of linking weights from input to hidden layer and from hidden to output layer, respectively. f_1 and f_2 are the transfer functions for hidden node and output node, respectively. Similar to the logistic regression, for each model, the study predicts the bankruptcy for three years prior to bankruptcy, two years prior to bankruptcy and one year prior to bankruptcy. All the networks used in this study have one hidden layer as it is

deemed to be sufficient for MLP network and also in order not to overtrain the network (Ashiquzzaman *et al.*, 2017).

Additionally, the study use the Neural Interpretation Diagram (NID) and Garson's algorithm method to aid in the interpretation of connection weights and determined the relative importance and contribution of each input variable in the networks. These approaches have been used by researchers (Aoki & Komatsu, 1999; Aurelle *et al.*, 1999, Brosse *et al.* 2001; Chen & Ware, 1999) to understand neuron connections in networks. Ozesmi and Ozesmi (1999) propose the Neural Interpretation Diagram (NID) to provide a visual interpretation of the connection weights among neurons, where the relative magnitude of each connection weight is represented by line thickness (thicker lines representing greater weights) and line shading represents the direction of the weight (black lines representing positive, excitatory signals and gray lines representing negative, inhibitor signals). Tracking the magnitude and direction of weights between neurons enables researchers to identify individual and interacting effects of the input variables on the output.

Garson (1991) proposed a method to partitioning the neural network connection weights in order to determine the relative importance of each input variable in the network. The basic idea is that the relative importance (or strength of association) of a specific explanatory variable for a specific response variable can be determined by identifying all weighted connections between the nodes of interest. All weights connecting the specific input node that pass through the hidden layer to the specific response variable are identified. This is repeated for all the other explanatory variables. The connections are tallied for each input node and scaled relative to all

other inputs. A single value is obtained for each explanatory variable that describes the relationship with response variable in the model. It is important to note that Garson's algorithm uses the absolute values of the connection weights when calculating variable contributions, and therefore does not provide the direction of the relationship between the input and output variables.

3.5.3 Endogeneity

The econometric problems of endogeneity have recently gained awareness within accounting and finance literature (Börsch-Supan & Köke, 2002; Chenhall & Moers, 2007; Larcker & Rusticus, 2005). A variable is said to be endogenous if it is determined within the context of the model, whilst a variable is said to be exogenous if it is correlated with the dependent variable, but its value is determined outside the model (Chenhall & Moers, 2007). In brief, an endogeneity problem arises when a variable that is originally assumed to be exogenous within a model is actually endogenous. Assume the following equation:

$$Y_t = \alpha + \beta X_t + \varepsilon_t \quad (13)$$

Statistically, the variable X_t is said to be endogenously related to the variable Y_t if X_t is correlated with the structural error term, ε_t , that is., $\text{Cov}(X_t, \varepsilon_t) \neq 0$ (Wooldridge, 2002). There are four major causes of endogeneity: omitted variables, simultaneity or reverse causation, measurement errors, and equilibrium conditions (Wooldridge, 2002; Chenhall & Moers, 2007; Larcker & Rusticus, 2005).

While endogeneity is predominant across many aspects of corporate finance, the relationship between some corporate governance indicators and bankruptcy may likely be infiltrated with endogeneity problem (Miglani, Ahmed & Henry, 2015;

Schultz, Tan & Walsh, 2015). Simultaneity or reverse causation arises when one or more of the independent variables are also simultaneously determined by the dependent variable (Wooldridge, 2002). This suggest that not only corporate governance indicators may cause bankruptcy, but also bankruptcy may trigger changes in corporate governance simultaneously.

Accordingly, it is reasonable to believe that as bankruptcy approaches, there would be potential changes to the corporate governance practices of those firms. However, with a limited access to most of the SMEs data, the study is limited to assessing the possibility of endogeneity problem with regards to some of the governance variables. This study hypothesises that corporate governance indicators such as number of directors in board (NDIR), proportion of independent directors in board (IND) and managing director-duality (MDD) affect bankruptcy. However, these corporate governance indicators and bankruptcy maybe endogenously determined. Therefore, it is important to take endogeneity into account as the presence of unobserved influences is likely to generate a degree of correlation between regressors and the error terms, which leads to biased estimates of the regressors' coefficients. The possible endogeneity could be due to cost cutting strategy in order to save resources to further strengthen the SMEs business operations. For example, the firms might find it difficult to retain an independent director due to the benefits and costs involve. Similarly, the firms might also merge some directors' responsibilities such as having single person to handle the position of managing director as well as the chairman of the board. Additionally, in the wake of financial difficulties, the firms might also decide to reduce the number of directors on board in order to save cost among others.

To test for endogeneity, this study estimates a linear probability model by two-stage least square (2SLS) method (Soderbom, 2009). The application of 2SLS regression is also supported by Miguel, Shanker and Ernest (2004). Furthermore, as Wooldridge (2002, p.472) says, "*this procedure is relatively straightforward and might provide a good estimate of the average effect.*" Test of endogeneity will be on model 2 and model 3 as they are the models that include the corporate governance variables.

These methods require an instrumental variable (IV) that is correlated with the corporate governance indicators, but does not affect bankruptcy. However, identifying appropriate instruments for corporate governance attributes is far more challenging (Larcker et al., 2007) especially in the context of SMEs due to the non-availability of some corporate information. More so, the literature does not extensively cover on the problem of endogeneity in relation to bankruptcy and corporate governance indicators. As such there is little guide in finding appropriate instruments for individual corporate governance characteristics.

Table 3.3

Definition of instrumental variables

Instrumental Variables	Measurement	Cited by
IND_NDIR	Measure of industry average for number of directors at end of the year	Ali, Liu & Su, (2014); Schultz et al., (2015)
IND_IND	Measure of industry average for proportion of independent directors at end of the year	Ali et al., (2014); Schultz et al., (2015)
DIR%Own	Measure of average percent of shares owned by directors	Bhagat & Bolton, (2008)

As presented in table 3.3, the study uses industry-average number of directors (IND_NDIR) as IV for NDIR and industry-average proportion of independent directors (IND_IND) as IV for IND (Ali et al., 2014; Schultz et al., 2015). The idea behind the industry IVs is that, the bankruptcy of a specific firm may effect on its own corporate governance, but it is unlikely to be identified with industry-level corporate governance. A company's manager may have the capacity to affect the corporate governance of their own firm yet they ought to have little, if any, impact on the corporate governance of other firms (Schultz et al., 2015). Industry-level IVs should work as valid instruments since they are identified with firm-level corporate governance but are unlikely to be identified with firm-level bankruptcy. This study further uses average percentage of shares owned by directors (DIR%Own) as IV for MDD (Bhagat & Bolton, 2008) and proportion of firm's tangible assets (TNGASSET) as an instrument for bankruptcy (Miglani et al., 2015). Finally, this study test the validity of the IVs in the empirical analysis. The first system of the simultaneous equations is specified as follows:

Model 2

$$IND_{i,t} = \alpha_0 + \beta_1 Z_{i,t} + \beta_2 CONT_{i,t} + \beta_3 NDIR_{i,t} + \beta_4 GENDER_{i,t} + \beta_5 MDD_{i,t} + \beta_6 MDEH_{i,t} + \beta_7 GDP_t + \beta_8 EMPY_t + \beta_9 LNR_t + \beta_{10} CPI_t + \beta_{10} IND_IND_t + \beta_{10} TNGASSET_{i,t} + \mu_t \quad (14)$$

$$NDIR_{i,t} = \alpha_0 + \beta_1 Z_{i,t} + \beta_2 CONT_{i,t} + \beta_3 IND_{i,t} + \beta_4 GENDER_{i,t} + \beta_5 MDD_{i,t} + \beta_6 MDEH_{i,t} + \beta_7 GDP_t + \beta_8 EMPY_t + \beta_9 LNR_t + \beta_{10} CPI_t + \beta_{10} IND_NDIR_t + \beta_{10} TNGASSET_{i,t} + \mu_t \quad (15)$$

$$\begin{aligned} \text{MDD}_{i,t} = & \alpha_0 + \beta_1 Z_{i,t} + \beta_2 \text{CONT}_{i,t} + \beta_3 \text{IND}_{i,t} + \beta_4 \text{GENDER}_{i,t} + \beta_5 \text{NDIR}_{i,t} + \beta_6 \text{MDEH}_{i,t} \\ & + \beta_7 \text{GDP}_t + \beta_8 \text{EMPY}_t + \beta_9 \text{LNR}_t + \beta_{10} \text{CPI}_t + \beta_{10} \text{DIR\%OWN}_{i,t} + \beta_{10} \text{TNGASSET}_{i,t} + \\ & \mu_t \end{aligned} \quad (16)$$

Model 3

$$\begin{aligned} \text{IND}_{i,t} = & \alpha_0 + \beta_1 Z_{i,t} + \beta_2 \text{EBIT}_{i,t} + \beta_3 \text{ROE}_{i,t} + \beta_4 \text{TLA}_{i,t} + \beta_5 \text{LTA}_{i,t} + \beta_6 \text{CLA}_{i,t} + \beta_7 \text{CLE}_{i,t} \\ & + \beta_8 \text{LQTI}_{i,t} + \beta_9 \text{WCT}_{i,t} + \beta_{10} \text{NWC}_{i,t} + \beta_{11} \text{AST}_{i,t} + \beta_{12} \text{EXP}_{i,t} + \beta_{13} \text{LogTA}_{i,t} + \\ & \beta_{14} \text{LogCAP}_{i,t} + \beta_{15} \text{AGE}_{i,t} + \beta_{16} \text{BLC}_{i,t} + \beta_{17} \text{CONT}_{i,t} + \beta_{18} \text{NDIR}_{i,t} + \beta_{19} \text{GENDER}_{i,t} + \\ & \beta_{20} \text{MDD}_{i,t} + \beta_{21} \text{MDEH}_{i,t} + \beta_{22} \text{GDP}_t + \beta_{23} \text{EMPY}_t + \beta_{24} \text{LNR}_t + \beta_{25} \text{CPI}_t + \beta_{26} \text{IND_IND}_t \\ & + \beta_{27} \text{TNGASSET}_{i,t} + \mu_t \end{aligned} \quad (17)$$

$$\begin{aligned} \text{NDIR}_{i,t} = & \alpha_0 + \beta_1 Z_{i,t} + \beta_2 \text{EBIT}_{i,t} + \beta_3 \text{ROE}_{i,t} + \beta_4 \text{TLA}_{i,t} + \beta_5 \text{LTA}_{i,t} + \beta_6 \text{CLA}_{i,t} + \\ & \beta_7 \text{CLE}_{i,t} + \beta_8 \text{LQTI}_{i,t} + \beta_9 \text{WCT}_{i,t} + \beta_{10} \text{NWC}_{i,t} + \beta_{11} \text{AST}_{i,t} + \beta_{12} \text{EXP}_{i,t} + \beta_{13} \text{LogTA}_{i,t} + \\ & \beta_{14} \text{LogCAP}_{i,t} + \beta_{15} \text{AGE}_{i,t} + \beta_{16} \text{BLC}_{i,t} + \beta_{17} \text{CONT}_{i,t} + \beta_{18} \text{NDIR}_{i,t} + \beta_{19} \text{GENDER}_{i,t} + \\ & \beta_{20} \text{MDD}_{i,t} + \beta_{21} \text{MDEH}_{i,t} + \beta_{22} \text{GDP}_t + \beta_{23} \text{EMPY}_t + \beta_{24} \text{LNR}_t + \beta_{25} \text{CPI}_t + \\ & \beta_{26} \text{IND_NDIR}_t + \beta_{27} \text{TNGASSET}_{i,t} + \mu_t \end{aligned} \quad (18)$$

$$\begin{aligned} \text{MDD}_{i,t} = & \alpha_0 + \beta_1 Z_{i,t} + \beta_2 \text{EBIT}_{i,t} + \beta_3 \text{ROE}_{i,t} + \beta_4 \text{TLA}_{i,t} + \beta_5 \text{LTA}_{i,t} + \beta_6 \text{CLA}_{i,t} + \\ & \beta_7 \text{CLE}_{i,t} + \beta_8 \text{LQTI}_{i,t} + \beta_9 \text{WCT}_{i,t} + \beta_{10} \text{NWC}_{i,t} + \beta_{11} \text{AST}_{i,t} + \beta_{12} \text{EXP}_{i,t} + \beta_{13} \text{LogTA}_{i,t} + \\ & \beta_{14} \text{LogCAP}_{i,t} + \beta_{15} \text{AGE}_{i,t} + \beta_{16} \text{BLC}_{i,t} + \beta_{17} \text{CONT}_{i,t} + \beta_{18} \text{NDIR}_{i,t} + \beta_{19} \text{GENDER}_{i,t} + \\ & \beta_{20} \text{MDD}_{i,t} + \beta_{21} \text{MDEH}_{i,t} + \beta_{22} \text{GDP}_t + \beta_{23} \text{EMPY}_t + \beta_{24} \text{LNR}_t + \beta_{25} \text{CPI}_t + \\ & \beta_{26} \text{DIR\%OWN}_{i,t} + \beta_{27} \text{TNGASSET}_{i,t} + \mu_t \end{aligned} \quad (19)$$

As discussed further in chapter four, in the first stage¹⁷, each equation from equation 14 to 19 is estimated with its respective IV, and the resulting predicted values are

¹⁷ In the first stage, each explanatory variable that is an endogenous covariate in the equation of interest is regressed on all exogenous variables in the model, including both exogenous covariates in the equation of interest and the excluded instruments.

saved. In the second stage¹⁸, each corporate governance mechanism is replaced with its saved predicted instrument from the first stage estimations in equation (5) and (6) and a logistic regression will be performed.

3.6 Chapter Summary

The chapter discusses the research methodology used in this study. The sample for this thesis is the SMEs in the manufacturing sector of Nigeria and Malaysia. The initial sample was 1,556 SMEs for Malaysia and 632 SMEs for Nigeria for the period 2000 to 2014. The research framework is discussed and explained together with the components. Based on the literature review, the chapter describes how the variables are selected and measured. Furthermore, the chapter explains on the research hypotheses that are formulated based on the research objectives. Finally, the chapter discusses on the methods that are used in the analysis in order to fulfil the objective of the study.

¹⁸ In the second stage, the regression of interest is estimated as usual using logistic regression, except that in this stage each endogenous covariate is replaced with the predicted values from the first stage.

CHAPTER 4

EMPIRICAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results of the empirical analysis. It is organised as follows. It presents the country specific analysis in the following order. Firstly, descriptive analysis is carried out to understand the mean differences of the predictors used for both bankrupt and non-bankrupt SMEs samples. Then, diagnostic tests such as the multicollinearity test (the Pearson correlation test to understand the relationship between the independent variables and the strength of their linear association), the model fit test and model specification test are performed for the logistic regression. The models are developed using logistic regression and artificial neural networks (ANNs) for each of the 1-year, 2-year and 3-year prior to bankruptcy samples using financial, non-financial, governance and macroeconomic variables. Robustness test for endogeneity is also carried out for model 2 and model 3 that contain corporate governance variables. The last section summarises and concludes the chapter.

4.2 Malaysian SMEs

The first part of the country analysis is on Malaysian data set for the 1-year, 2-year and 3-year prior to bankruptcy samples. The analysis predicts bankruptcy among SMEs in Malaysia and compared the predictive accuracy rate of each model developed using logistic regression and ANN.

4.2.1 Descriptive Statistics of Malaysian Sample

The descriptive statistics of the variables used to estimate the logistic regression and the ANN model between the bankrupt and non-bankrupt SMEs are presented in

table 4.1, 4.2 and 4.3. Univariate analysis is carried out to identify the variables that have the highest ability to differentiate between the bankrupt and non-bankrupt SMEs for the 3-year, 2-year and 1-year prior to bankruptcy samples. The results of the 3-year prior to bankruptcy sample (table 4.1) show that ROE, TLA, CLE, LogCAP, AGE, BLC, GENDER, MDD, NDIR, IND, CONT, MALAY and FOREIGN have a significant mean difference at the 1 percent level between the bankrupt and non-bankrupt SMEs. However, the variables EBIT, NWC and INDIAN between the bankrupt and non-bankrupt SMEs are significant at the 5 percent level.

The p-values for the variables EBIT, ROE, TLA, CLE, LQT, LogCAP, AGE, BLC, GENDER, MDD, NDIR, IND, CONT, MALAY and FOREIGN are less than 0.01 for the 2-year prior to bankruptcy sample (table 4.2). Thus, there is a significant difference between bankrupt and non-bankrupt SMEs. The variables LTA, WCT and INDIAN are significantly different at the 5 percent level between bankrupt and non-bankrupt SMEs. Additionally, AST and CTA are significantly different at the 10 percent level between the bankrupt and non-bankrupt SMEs. The p-value for the variables EBIT, TLA, CLE, LQT, AST, LogCAP, LogTA, AGE, BLC, GENDER, MDD, NDIR, CONT, FOREIGN and MALAY are less than 0.01 for the 1-year prior to bankruptcy sample (table 4.3), thus there is a significant difference between the bankrupt and non-bankrupt SMEs. The p-value of NWC is significant at the 5 percent level.

Table 4.1
Descriptive Statistics of Malaysia Sample

3-year prior to bankruptcy Sample					
	Bankrupt SMEs		Non- Bankrupt SMEs		
Variables	Mean	St. D	Mean	St. D	p-value
EBIT	-0.2365	2.1999	1.0166	0.316	0.014**
ROE	-0.0099	1.3106	2.4463	0.234	0.00***
TLA	0.9406	0.8493	0.5083	0.491	0.00***
LTA	0.4136	0.4310	0.3625	0.417	0.507
CTA	0.3052	0.5824	0.3289	0.604	0.618
CLE	0.8332	0.8714	0.6448	0.609	0.00***
LQT	3.1068	19.006	2.6982	18.80	0.430
WCT	2.0031	18.814	1.3211	18.06	0.254
NWC	-60054	68537	506331	6971	0.031**
AST	1.5051	1.3694	1.6732	1.471	0.262
EXP	1.3368	3.6605	0.7281	6.283	0.486
LogTA	14.690	2.1688	14.198	2.233	0.163
LogCAP	12.328	3.4314	11.069	4.170	0.00***
AGE	12.614	7.0152	25.954	14.13	0.00***
BLC	0.6109	0.4883	0.7003	0.458	0.01***
GENDER	0.8298	0.3764	0.5719	0.495	0.00***
MDD	0.3495	0.4776	0.1346	0.341	0.00***
NDIR	2.3799	0.7601	2.8532	1.016	0.00***
IND	0.2639	0.4050	0.2306	0.352	0.00***
CONT	0.7264	0.4465	0.4801	0.500	0.00***
CHINESE	0.5745	0.4952	0.6055	0.489	0.164
FOREIGN	0.0699	0.2554	0.1865	0.390	0.00***
INDIAN	0.0790	0.2702	0.0581	0.234	0.031**
MALAY	0.2310	0.4221	0.1498	0.357	0.00***
N	329	329	327	327	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY). Number of observation (N)

Table 4.2
Descriptive Statistics of Malaysia Sample

Variables	2-year prior to bankruptcy Sample				p-value
	Bankrupt SMEs		Non- Bankrupt SMEs		
	Mean	St. D	Mean	St. D	
EBIT	-0.2897	0.6125	0.0757	0.211	0.00***
ROE	-0.6864	1.8487	0.1381	1.030	0.00***
TLA	1.6768	1.4827	0.6563	0.345	0.00***
LTA	0.1134	0.1416	0.1471	0.171	0.02**
CTA	1.0959	3.3812	0.7806	0.575	0.084*
CLE	1.8227	2.6548	0.7841	1.890	0.00***
LQT	0.9979	0.8563	1.2974	1.992	0.00***
WCT	-0.0181	0.7483	0.1940	1.623	0.02**
NWC	-66833	80340	575660	7625	0.248
AST	1.6650	1.8751	8.7369	1.656	0.061*
EXP	2.3749	18.114	2.0888	19.36	0.834
LogTA	14.626	2.2083	14.013	2.185	0.251
LogCAP	12.080	3.8448	10.339	4.663	0.00***
AGE	12.314	6.6771	25.693	13.68	0.00***
BLC	0.6000	0.4909	0.7277	0.446	0.00***
GENDER	0.8298	0.3766	0.5830	0.494	0.00***
MDD	0.2596	0.4393	0.1149	0.319	0.00***
NDIR	2.3064	0.6729	3.0766	1.241	0.00***
IND	0.2817	0.4184	0.2468	0.376	0.01***
CONT	0.7447	0.4370	0.5021	0.501	0.00***
CHINESE	0.5957	0.4918	0.6128	0.488	0.453
FOREIGN	0.0809	0.2732	0.1787	0.383	0.00***
INDIAN	0.0851	0.2796	0.0596	0.237	0.033**
MALAY	0.2383	0.4270	0.1489	0.356	0.00***
N	235	235	235	235	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY). Number of observation (N)

Table 4.3
Descriptive Statistics of Malaysia Sample

Variables	1-year prior to Bankruptcy Sample		Non- Bankrupt SMEs		p-value
	Bankrupt SMEs		Non- Bankrupt SMEs		
	Mean	St. D	Mean	St. D	
EBIT	-0.2078	0.5248	-0.0171	0.321	0.00***
ROE	-0.8398	2.1270	0.6075	2.186	0.598
TLA	0.8424	0.7940	0.4919	0.373	0.00***
LTA	0.1546	0.2316	0.1258	0.340	0.962
CTA	0.8041	0.4294	0.7664	0.497	0.108
CLE	2.1342	1.7748	1.2457	1.419	0.00***
LQT	0.9913	1.4192	1.5223	1.276	0.00***
WCT	0.0136	1.3810	0.1014	0.952	0.305
NWC	-1600002	77294	-316572	4378	0.015**
AST	0.5729	0.3398	1.7699	1.404	0.00***
EXP	1.0413	0.4295	1.0322	0.381	0.962
LogTA	14.6737	2.0149	13.6971	2.746	0.00***
LogCAP	12.3866	3.2975	10.3428	4.757	0.00***
AGE	14.6507	7.8549	26.5238	12.70	0.00***
BLC	0.6124	0.4884	0.7429	0.438	0.00***
GENDER	0.8469	0.3610	0.6000	0.491	0.00***
MDD	0.4019	0.4915	0.1048	0.307	0.00***
NDIR	2.3732	0.7367	3.0619	1.233	0.00***
IND	0.2617	0.3988	0.2436	0.376	0.401
CONT	0.7225	0.4488	0.5143	0.501	0.00***
CHINESE	0.6124	0.4884	0.6095	0.489	0.999
FOREIGN	0.0622	0.2421	0.1714	0.377	0.00***
INDIAN	0.0670	0.2506	0.0667	0.250	0.999
MALAY	0.2584	0.4388	0.1524	0.360	0.00***
N	209	209	210	210	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY). Number of observation (N)

The result suggests that bankrupt SMEs rely heavily on debt financing. The total debt (TLA) is approximately 94 percent, 167 percent and 84 percent in the respective 3-year, 2-year and 1-year prior to bankruptcy samples. However, for non-bankrupt SMEs, TLA shows only 51 percent, 66 percent and 49 percent for the

respective years. The closer the companies move into bankruptcy, the higher the liabilities in supporting the assets as evident in the results. However, the shortcoming of the TLA is that it does not provide any indication of assets quality, since the total assets is sum of tangible and intangible asset together. The possible reasons of higher debt obligations could also be that the higher assets value comes from the intangible assets like goodwill, royalty, and copyright among others. The findings from the descriptive analysis shows that bankrupt SMEs are not performing well as expected, those intangible assets will have to be written off. Thereby having more debt obligation compared to the total assets. Similar finding is reported by Abdullah et al. (2016), Altman et al. (2010) and Behr and Guttler (2007). The high reliance on debts has reflected on the bankrupt SMEs' profitability. The companies appear to be less profitable compared to the non-bankrupt SMEs in all the estimated samples.

The profitability of non-bankrupt SMEs (EBIT) is 102 percent, 7.6 percent and -2 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. While the profitability of bankrupt SMEs is -24 percent, -29 percent and -21 percent for the respective sample. This could probably be as a result of the high level of obligations and commitments the companies have to fulfil which may trim their earnings. As the bankruptcy approaches, the profitability of the bankrupt companies decreases as evident in the descriptive analysis. Abdullah et al. (2016) also find a similar trend on the decreasing of profitability as the companies move closer to bankruptcy by Malaysian SMEs.

Bankrupt SMEs' liquidity (LQT) is much lower compared to non-bankrupt SMEs which is 0.99 times versus 1.42 times and 0.99 times versus 1.30 for 1-year and 2-year prior to bankruptcy samples respectively. However, the liquidity of the bankrupt SMEs is higher for the 3-year prior to bankruptcy sample compared to that of non-bankrupt SMEs, 3.11 times versus 2.70. This could be as a result of cash generated from disposal of company assets to support their business operation in the wake of financial difficulties. Furthermore, companies could also be selling off the company's assets in order to service their debt obligations (Tanthanongsakkun, Pitt & Treepongkaruna, 2007). Company's liquidity position is among the most important factor in assessing the likelihood of bankruptcy. A company may be suffering from poor operating performance or troubled balance sheet, but it will not become truly distressed until it is unable to continue financing its operations. Both bankrupt and non-bankrupt SMEs are considered to be incurring high operating expenses (EXP) in their day-to-day business operations. High operational expenses affect companies' profitability and highlight the extent of managerial discretion in spending company resources.

Moreover, bankrupt SMEs are considered to be younger compared to non-bankrupt SMEs. The average age for bankrupt SMEs is between 12 to 14 years whereas non-bankrupt SMEs is more than 26 years. Long established companies would likely have more developed valuable resources and capabilities in their evolution from being young to being mature, while young companies are more likely to suffer from resource and capability deficiencies (Thornhill & Amit, 2003). The results further show that majority of non-bankrupt SMEs in Malaysia are having business operation in more industrialised states such as Selangor, Kuala Lumpur, Johor,

Sarawak and Pulau Pinang. However, bankrupt SMEs are mostly located in less industrialised states¹⁹ in Malaysia.

More so, the results indicate that majority of the bankrupt and non-bankrupt SMEs are managed by male managing directors (GENDER) for the respective 1-year (84 percent versus 60 percent), 2-year (83 percent versus 58 percent) and 3-year (83 percent versus 57 percent) prior to bankruptcy samples. Bankrupt SMEs are having a high number of duality (MDD) in their board composition compared to non-bankrupt SMEs. Managing director duality between the bankrupt and non-bankrupt SMEs is 40 percent versus 10 percent, 25 percent versus 11 percent and 35 percent versus 13 percent for their respective 1-year, 2-year and 3-year prior to bankruptcy samples. Malaysian Code on Corporate Governance (MCCG, 2017) recommends that different individuals should hold the positions of chairperson and CEO as doing so promotes accountability and facilitates division of responsibilities between them. The responsibilities of the chairperson should include leading the board in the oversight of management, while the CEO focuses on the business and day-to-day management of the company.

The average board size for non-bankrupt SMEs is 3 directors while for bankrupt SMEs, the average board size is 2 directors for all the prior year to bankruptcy samples (1-year, 2-year and 3-year prior to bankruptcy samples). For bankrupt SMEs, 72, 74 and 73 percent of the SMEs, for the respective 1-year, 2-year and 3-year prior to bankruptcy samples are having controlling shareholders. However, for

¹⁹ Sabah, Malacca, Perak, Kedah, Kelantan, Pahang, Terengganu, Negeri Sembilan and Perlis. For more details on Malaysian states, please refer to the following link <http://www.nationsonline.org/oneworld/States-of-Malaysia.htm>

non-bankrupt SMES only 51, 50 and 48 percent of the non-bankrupt SMEs are having controlling shareholder for 1-year, 2-year and 3-year prior to bankruptcy samples respectively. Furthermore, Chinese managing directors on average are managing 60 percent of bankrupt SMEs, then followed by Malay managing directors with 24 percent, Indian managing directors with 8 percent and foreign managing directors with 7 percent. Additionally, both bankrupt and non-bankrupt SMEs have independent directors as their board members. On average, bankrupt SME's board consists of about 27 percent of independent members while non-bankrupt SMEs have about 24 percent of independent directors. The presence of independent directors is also recommended by MCCG (2017) as independent directors bring independent and objective judgment to the board and this lessens risks arising from conflict of interest or undue influence from interested parties.

4.2.2 Diagnostic Tests for Logistic Regression

This section presents the diagnostic tests to ensure that the assumptions of the logistic regression model are met. The diagnostic tests include multicollinearity test, model fit test and model specification test.

4.2.2.1 Multicollinearity

Pearson correlation test is conducted for the independent variables. The results in table 4.4 shows that majority of the correlations of the variables are moderately low ranging from 0.0002 to 0.979. However, the correlation between LQT against WCT is 0.979. The high correlation is not a concern for the study as the variance inflating factor (VIF) between the variables ($LQT = 2.358$ and $WCT = 2.604$) is not above the critical value of 10.

Table 4.4

Pearson Correlation Analysis of Malaysian Sample

	EBIT	ROE	TLA	LTA	CTA	CLE	LQT	WCT	NWC	AST	EXP	LogT A	LogCA P	AGE
EBIT	1													
ROE	.359***	1												
TLA	-.097	-.21**	1											
LTA	-.006	-.09**	.061	1										
CTA	.009	-.06	.093**	.211***	1									
CLE	-.020	-.116	.092**	.035	-.03	1								
LQT	.004	.015	.009	.007	.01	-.03	1							
WCT	.000	-.001	.012	.015	.01	-.03	.979***	1						
NWC	.037	.168***	-.020	-.050	-.06	-.04	.127***	.027	1					
AST	-.005	.073	-.030	.086**	-.05	-.01	.047	.048	-.00	1				
EXP	-.028	-.075	.034	-.010	.01	-.01	.003	.004	-.02	.028	1			
LogTA	.167	-.021	.073	-.030	.016	-.02	-.001	-.02	.05	.047	.019	1		
LogCAP	.014	-.085	.078**	-.035	-.02	-.05	.055	.049	.03	-.04	-.03	.596	1	
AGE	.194	.414***	-.079	-.052	.01	-.03	.077**	.053	.05	.027	-.02	.022	.005	1
BLC	.041	.088**	-.014	-.050	-.01	-.02	.020	.018	.08	.005	-.06	-.04	-.11	.080
GENDER	-.132	-.21	.091**	-.070	-.08	.054	.023	.016	.01	-.08	.019	.032	.126	-.16
MDD	-.042	-.160	.140**	-.031	-.05	-.01	-.032	-.03	-.02	-.01	.000	.034	.099	-.14
NDIR	.014	.232***	-.082	-.053	-.01	-.06	-.045	-.05	.05	-.03	.004	.070	.037	.207
IND	-.052	-.052	.030	.032	-.01	.000	-.032	-.05	.01	.035	.015	.212	.126	.057
CONT	-.114	-.15	.092**	-.029	-.01	-.02	.074	.066	.03	-.02	.030	.150	.174	-.18
CHINESE	.000	-.001	-.049	-.095	.07	-.01	.006	.004	.02	.08	.031	.007	-.05	.085
FOREIGN	.078**	.155***	-.022	.040	-.02	.015	-.028	-.03	.02	-.07	-.11	.091	.072	.048
INDIAN	-.065	.003	-.020	.020	-.03	-.06	.008	.001	.08	-.07	-.00	-.11	-.08	-.06
MALAY	-.016	-.105	.003	.018	-.08	-.04	.021	.027	-.06	.015	.055	-.04	.051	-.11
CPI	.034	.066	.022	.020	-.02	.004	-.005	-.02	.06	.018	-.04	.020	-.01	.08
GDP	-.035	-.116	-.051	-.027	.003	-.02	-.010	.003	-.04	.020	.012	.046	.044	-.07
LNR	.010	.076	.028	.014	-.03	-.07	.017	.016	.02	-.02	-.02	.025	-.00	.084
EMPY	-.026	-.072	-.009	-.050	.022	.041	-.009	-.00	-.08	.025	.042	-.05	-.00	-.11

Table 4.4 (continued)

Variables	BLC	GENDER	MDD	NDIR	IND	CONT	CHIN ESE	FOREI GN	INDIA N	MALA Y	CPI	GDP	LNR	EMP Y
BLC	1													
GENDER	.103	1												
MDD	-.091	.096	1											
NDIR	.055	-.156	-.131	1										
IND	.014	.081	-.231	.145	1									
CONT	-.021	.119	.2311	.021	.246	1								
CHINESE	-.062	-.070	.0911	-.151	-.193	-.120	1							
FOREIGN	.037	.112	-.171	.090	.151	-.011	-.454	1						
INDIAN	-.013	-.061	-.060	.059	-.033	.010	-.312	-.102	1					
MALAY	.014	.032	.050	.054	.093	.122	-.566	-.188	-.130	1				
CPI	.008	-.065	-.030	.049	.075	.005	-.013	.099	.054	-.076	1			
GDP	.024	.063	.061	-.042	.048	-.033	-.011	-.023	-.047	.039	-.426	1		
LNR	.029	-.093	.010	.074	-.023	.007	-.042	.059	.035	-.007	.359	-.096**	1	
EMPY	-.030	.061	-.021	-.054	.011	.017	.045	-.090	-.024	.029	-.407	.127***	-.574	1

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY).

Majority of the correlation between the independent variables are insignificant. However, some of the variables such as EBIT against ROE, EBIT against FOREIGN, ROE against TLA, ROE against LTA, ROE against NWC, ROE against AGE, ROE against NDIR, ROE against FOREIGN, TLA against CTA, TLA against CLE, TLA against LogCAP, TLA against GENDER, TLA against MDD, TLA against CONT, LTA against CTA, LTA against AST, LQT against WCT, LQT against NWC, LQT against AGE, GDP against LNR and GDP against EMPY are found to be significant. The moderately low pairwise correlation among the variables indicates that multicollinearity is not a threat to this study.

Table 4.5
Variance inflating factor

Variables	R ²	VIF = 1/(1-R ² _j)
EBIT	0.140	1.163
ROE	0.148	1.173
TLA	0.117	1.132
LTA	0.111	1.125
CTA	0.313	1.455
CLE	0.171	1.206
LQT	0.576	2.358
WCT	0.616	2.604
NWC	0.211	1.267
AST	0.302	1.433
EXP	0.169	1.204
LogTA	0.443	1.794
LogCAP	0.542	2.126
AGE	0.177	1.179
BLC	0.037	1.038
GENDER	0.122	1.139
MDD	0.235	1.307
NDIR	0.166	1.199
IND	0.286	1.401
CONT	0.104	1.116
CHINESE	0.770	4.348
FOREIGN	0.629	2.695
INDIAN	0.253	1.339
MALAY	0.714	3.497
CPI	0.309	1.447
GDP	0.223	1.287
LNR	0.347	1.531

Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY).

To further verify that multicollinearity is not a problem to this study, VIF is reported in table 4.5. If the variables have VIF values greater than 10 or tolerance values lower than 0.10, then they are considered to have multicollinearity problems (Gujarati, 2003). Since all the variables have VIF values that are approximately 1.038 to 4.348, this suggest that no multicollinearity problem exists.

4.2.2.2 Model Specification Test

This subsection discusses the specification error test²⁰. The study uses the linktest for the model specification error test. The idea behind Linktest is that if the model is properly specified, one should not be able to find any additional predictors that are statistically significant except by chance. Linktest uses the linear predicted value

²⁰ When a logistic regression model is build, the assumption is that the logit function of the outcome variable is a linear combination of the independent variables. This includes two aspects, i.e. the two sides of the logistic regression equation. First, consider the link function of the outcome variable on the left hand side of the equation. The assumption is that the logit function (in logistic regression) is the correct function to use. Secondly, on the right hand side of the equation, the assumption is that all the relevant variables included in the model, and the logit function is a linear combination of the predictors. It could happen that the logit function as the link function is not the correct choice or the relationship between the logit of outcome variable and the independent variables is not linear. In either case, we have a specification error. The misspecification of the link function is usually not too severe compared with using other alternative link function choices such as probit (based on the normal distribution). In this study, we are more concerned with whether our model has all the relevant predictors and if the linear combination of them is sufficient (Gujarati, 2003; Pregibon, 1980).

(\hat{y}) and linear predicted value squared (\hat{y}^2) as the predictors to rebuild the model. The variable \hat{y} should be a statistically significant predictor, since it is the predicted value from the model. This should be the case unless the model is completely misspecified (Pregibon, 1980).

On the other hand, if the model proposed in the study is properly specified, variable \hat{y}^2 should not have much predictive power except by chance. Therefore, to pass the linktest, it is expected that \hat{y}^2 should be insignificant (Pregibon, 1980). Table 4.6 presents the result of the Linktest which is the general model specification for non-linear regression models.

Table 4.6
Model Specification Test (Linktest) Malaysian Sample

	Model 1		Model 2		Model 3	
	Linktest	p-value	Linktest	p-value	Linktest	p-value
1-Year Prior	\hat{y}	0.000***	\hat{y}	0.000***	\hat{y}	0.000***
	\hat{y}^2	0.627	\hat{y}^2	0.899	\hat{y}^2	0.686
2-Year Prior	\hat{y}	0.000***	\hat{y}	0.000***	\hat{y}	0.000***
	\hat{y}^2	0.081*	\hat{y}^2	0.126	\hat{y}^2	0.121
3-Year Prior	\hat{y}	0.000***	\hat{y}	0.000***	\hat{y}	0.000***
	\hat{y}^2	0.110	\hat{y}^2	0.924	\hat{y}^2	0.496

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2.

The results show that model 1 (1-year and 3-year prior to bankruptcy samples), model 2 (1-year, 2-year and 3-year prior to bankruptcy samples) and model 3 (1-year, 2-year and 3-year prior to bankruptcy samples) are correctly specified.

However, model 1's 2-year prior sample $_hatsq$ is marginally significant at the 10 percent level. If $_hatsq$ is significant, then this usually means that either the study has omitted relevant variable(s) or the link function is not correctly specified. In general, the finding confirms that the study has selected meaningful predictors.

4.2.2.3 Test for Model Fit

The test for models fit is presented in table 4.7. The Hosmer–Lemeshow test²¹ is a statistical test for goodness of fit for logistic regression models. The test suggests that both models fit the data because the observed and expected event rates in subgroups are similar which indicates that the models are consistent with the data. This can be observed in the insignificant p-value of model 1 (0.940 and 0.598 for the respective 3-year and 1-year prior to bankruptcy samples), model 2 (0.464 and 0.250 for the respective 3-year and 1-year prior to bankruptcy samples) and model 3 (0.254 and 0.132 for respective 3-year and 1-year prior to bankruptcy samples). Thus, the predictors identified in this study could detect bankruptcy among SMEs in Malaysia. However, the 2-year prior to bankruptcy sample is statistically significant for each model indicating that the model do not fit the data that only includes corporate governance variables.

²¹ The test assesses whether or not the observed event rates match expected event rates in subgroups of the model population. The idea behind the Hosmer and Lemeshow's goodness-of-fit test is that the predicted frequency and observed frequency should match closely, and that the more closely they match, the better the fit (Hosmer & Lemeshow, 2013). It is widely used to answer the question on how well does the model fit the data.

Table 4.7

Model Fit Test Malaysian Sample

	Hosmer-Lemeshow Test		
	3-year Prior sample	2-year Prior sample	1-year Prior sample
Model 1	2.901 (0.940)	19.403 (0.013)**	6.443 (0.598)
Model 2	7.691 (0.464)	19.120 (0.014)**	14.217 (0.250)
Model 3	7.493 (0.254)	88.360 (0.000)***	11.691 (0.132)

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Numbers in parenthesis represent p-value.

4.2.3 Logistic Regression Analysis

To examine whether each of the independent variables can explain bankruptcy, a 0-1 dummy variable is regressed on the independent variables. The study present the results from logistic regression²² in table 4.8 while table 4.9 report the results of forecasting accuracy for both the bankrupt and non-bankrupt observations.

4.2.3.1 Model 1: Financial and Non-financial Variables

The result from the logistic regression is presented in table 4.8. Profitability (ROE), leverage (TLA) and age of SME (AGE) are the most influential financial variables in predicting bankruptcy among SMEs in Malaysia. The result shows a negative coefficient between SMEs profitability (ROE) and bankruptcy. The predictor is statistically significant at the 1 percent level for 3-year and 1-year prior to bankruptcy samples while at the 5 percent level for 2-year prior to bankruptcy sample. The finding indicates that high level of profitability lowers the probability of bankruptcy among the SMEs in Malaysia. The descriptive statistic also shows that non-bankrupt SMEs are more profitable compared to bankrupt SMEs. The result is consistent with the finding of Abdullah et al. (2016), Arslan and Karan

²² The results presented in table 4.8 show only the significant variables from the models. The full results (significant and non-significant variables) are presented in Appendix 1

(2009), Fidrmuc et al. (2006) and Fidrmuc and Hainz (2010). With enough profit, firms are able to retain part of the profit and reinvest to further strengthen the growth of the company. On the other hand, less profitable SMEs have to source outside funds to support their business operations such as debt financing. Based on pecking order theory, these funds are more expensive and cost ineffective compared to retained earnings (Myers, 1984). EBIT, another measure of profitability is also negatively related to bankruptcy but is only significant in the 2-year prior to bankruptcy sample. High profitability could be the key to SMEs survival. Firms that are not profitable in their business operations are likely to go bankrupt.

On the other hand, high amount of debt obligations would increase the financial risk of an SME. The result shows that leverage (TLA) is positively related to bankruptcy and is statistically significant at the 1 percent level for the 3-year, 2-year and 1-year prior to bankruptcy samples. The likelihood of defaulting on fixed obligations is high when there is high level of financial risk. Abdullah et al. (2016), Behr and Guttler (2007) and Chotima (2013) report a similar finding by using SMEs sample. Furthermore, higher level of leverage will result in a trade-off between interest tax shield enjoyed by the firm and an increase financial risk (Hirshleifer, 1966; Robichek & Myers, 1965). Consequently, there is a possibility of a firm facing bankruptcy. Therefore, the higher the leverage of an SME, the more likely it is to go bankrupt.

A negative coefficient is found between liquidity (LQT) and SME bankruptcy. It is statistically significant at the 10 percent level in the 3-year prior to bankruptcy sample and at the 1 percent level in the 1-year prior to bankruptcy sample. A

negative coefficient for liquidity suggests that the lower the liquidity the more likely an SME is to go bankrupt. A company's ability to turn short-term assets into cash to cover debts is of the utmost importance when creditors are seeking payment. Bankruptcy analysts frequently use liquidity ratios to determine whether a company is able to continue as a going concern. Insolvency increases the risk of firms failing to meet their financial commitments, which is likely to cause bankruptcy. As a precautionary measure, SMEs should maintain sufficient level of liquidity in order to fulfil their fixed obligations periodically. Consistent with previous studies (Abdullah et al., 2016; Chotima, 2013; Fidrmuc & Hainz 2010; Khorasgani, 2011; Monelos et al., 2011; Monelos et al., 2012; Moscalu 2012; Sirirattanaphonkun & Pattarathammas 2012), the higher the illiquidity, the higher the bankruptcy probability.

Size is also found to be significant in predicting business bankruptcy. Size (LogCAP) has a positive coefficient and statistically significant i.e. the bigger the size of a company, the higher is the probability of bankruptcy. The variables is significant at the 5 percent level for 3-year and 2-year prior to bankruptcy samples. It is likely that in some cases large asset based do not always imply high asset quality. For instance, a firm might have many trade debtors, but they are most likely problematic debtors with bad collection history. Other possibility might be a firm might have a large stock of inventory that cannot be sold due to less demand.

Table 4.8

Logistic regression of Malaysian Sample

Variables	Model 1			Model 2			Model 3		
	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	2.645**	-3.026*	3.991***	-0.398	0.544	-0.156	1.311	-1.023	1.914
ROE	-1.063***	-0.345**	-0.432***				-1.151***		-0.505***
EBIT		-6.407***						-6.770***	
TLA	1.591***	3.912***	1.200***				1.435***	4.534***	1.095***
LTA		-1.857*						-3.399***	
CTA	-0.328*	0.590**						0.618*	
LQT	-0.076*		-0.884***				-0.083*	-0.983*	-1.087***
WCT	0.021***		0.756***				0.018***	1.058**	0.940***
NWC	0.085*	0.024**						0.580*	0.106*
AST			-2.404***						-2.615**
LogCAP	0.077**	0.125**					0.054*	0.116*	
AGE	-0.170***	-0.159***	-0.124***				-0.168***	-0.168***	-0.131***
BLC	-0.454**		-0.712*				-0.546**		1.039**
MDD				0.966***	0.615**	1.429***	0.702***	1.415**	2.044***
CONT				0.843***	0.948***	0.856***	0.456*	0.977**	0.862**
NDIR				-0.609***	-1.097***	-0.893***	-0.482***	-1.575***	-0.578***
IND							0.827**		
GENDER				1.155***	1.258***	1.207***	1.142***	1.241**	1.112**
INDIAN				1.263***	1.673***	1.527***	2.058***		2.765***
MALAY				0.855***	1.151***	1.398***	1.367***		2.421***
CHINESE					0.584*		1.200***		
EMPY				2.615*		4.065***			
McFadden R ²	0.404	0.658	0.581	0.197	0.246	0.279	0.490	0.762	0.699
Observation (N)	534	376	336	534	376	336	534	376	336

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CTA), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY) and yearly percentage changes in unemployment rate (EMPY).

In addition, the results show a significant negative coefficient between SME age (AGE) and bankruptcy; and it is statistically significant at the 1 percent level for 3-year, 2-year and 1-year prior to bankruptcy samples. The finding suggests that the longer the existence of an SME, the higher the chance of it to survive. Probably the SME has vast experience and management capabilities (expertise). Firms are able to tap into the relevant customer segment and provide differentiated products that meet demand which will subsequently help them in gaining customer loyalty and build up better rapport with suppliers (Majumdar, 1997).

Long established companies are more likely to have competitive advantage and resource capabilities in their development stages from being young to being older, while young companies are more likely to suffer from resource and capability deficiencies (Thornhill & Amit, 2003). This could be as a result of several firm's activities over the years. For example, mergers, absorptions, evolution from micro, small, medium to large may have happened over the years. These situations would be quite common given the nature of SMEs business. Previous studies also find that age of company is negatively related to bankruptcy (Abdullah et al., 2016; Altman et al., 2010; Blanco et al., 2007; Shane, 1996). Therefore, increase in SMEs years of business operation decreases the likelihood of bankruptcy.

Furthermore, business location (BLC) is a negative and significant predictor of SMEs bankruptcy in Malaysia. The predictor is significant at the 5 percent level for the 3-year prior to bankruptcy sample and at the 10 percent level for the 1-year prior to bankruptcy sample. The results indicate that SMEs in less industrialised states are more likely to go bankrupt. Businesses in more industrialised location can benefit

more compared to their counterpart in less industrialised location. This is because developed location can be viewed as an enabler of resource acquisition and capability development as it can provide competitive advantages such as access to proactive business networks which include having good rapport with customers, suppliers and industry and government associations which are more likely to be in close proximity (Westhead et al., 2004). Furthermore, businesses in industrialised states have better access to good infrastructure facilities that help to ease processes of doing business (Eickelpasch et al., 2015). Government is likely to support more and has greater initiatives to develop the industrialised states as these states contribute significantly towards economic development of the country (Eickelpasch et al., 2015). Furthermore, government assistance is more reachable in developed states (Bennett & Smith, 2002).

Additionally, businesses located at industrialised states can benefit from favourable supply side conditions, access to skilled labour, financial institutions and technology partners (Fuller-Love et al., 2006; Westhead et al., 2004). Financial institution such as commercial banks may consider businesses in developed states as having less risk and provide lower interest rate compared to the businesses in other states that are less developed (Pofeldt, 2016). This is further supported by the descriptive statistics which show that SMEs in less industrialised states of Malaysia are more risky due to lower profit, lower liquidity, high leverage and are relatively younger compared to their counterparts in industrialised states.

4.2.3.2 Model 2: Governance and Macroeconomic Variables

The empirical evidence from table 4.8 demonstrate a strong influence of corporate governance variables in predicting bankruptcy among SMEs in Malaysia. The variables such as MDD, CONT, NDIR, GENDER, INDIAN and MALAY are statistically significant and appeared in all the prior year samples for model 2. Among the macroeconomic variables, only EMPY is statistically significant in the 3-year and 1-year prior to bankruptcy samples.

The result shows that the presence of managing director duality (MDD) has a significant and positive coefficient with bankruptcy. The predictor is statistically significant at the 1 percent level for the 3-year and 1-year prior to bankruptcy samples and at the 5 percent level for the 2-year to bankruptcy prior sample. The findings suggest that an SME with managing director who is also the chairman of the board is more likely to go bankrupt. Consistently, previous studies also find that CEO-duality has a positive correlation with company bankruptcy. CEO-duality lead to more controlling, lower levels of control and over-concentration of decision-taking functions (Argenti, 1986; Daily & Dalton, 1994; Hambrick & D'Aveni, 1992; Mallette & Fowler, 1992). Accordingly, agency theory argue that where the chief executive officer is the chairman of the board of directors, the impartiality of the board is compromised. The interests of the owners will be sacrificed to a degree in favour of the management, that is, there will be managerial opportunism and agency loss (Donaldson & Davis, 1991; Eisenhardt, 1989; Fama & Jensen, 1983; Jensen & Meckling 1976; Roe, 2004; Williamson, 1985). Moreover, MCCG (2017) recommends that the positions of chairman and chief executive officer should be

held by different individuals as doing so promotes accountability and facilitates division of responsibilities between them.

Board size (NDIR) is negatively related to bankruptcy and is significant at the 1 percent level for all the prior samples in predicting SMEs bankruptcy. The finding suggests that larger board can decrease the probability of bankruptcy among SMEs. With a large number of directors on board, SMEs would have access to diverse skills and experience from different members and monitor the managing director effectively on matters such as investment opportunities and improve business efficiency among others (Eisenberg, Sundgren, & Wells, 1998). The finding is also consistent with that of Abdullah et al. (2016) and Keasey and Watson (1987) where they find that the number of directors on the SME's board is negatively related to bankruptcy. Hence, the result shows that SMEs with small board size are more likely to go bankrupt.

Furthermore, the results show that controlling shareholder (CONT) has a positive coefficient and significant impact on predicting bankruptcy among SMEs in Malaysia. CONT is significant at the 1 percent level for the 2-year and 1-year prior to bankruptcy samples and at the 10 percent for the 3-year prior to bankruptcy sample. This indicates that the greater the holding of controlling shareholder, the higher is the likelihood of bankruptcy among SMEs. According to advocates of agency theory, when ownership concentration exceeds a certain level, controlling shareholder(s) tend to exercise their control rights to generate private benefits, sometimes at the expense of the minority shareholders (Abdullah et al., 2016; Ishak & Napier, 2006; La Porta, Lopez-de-Silanes, & Shleifer, 1999; Shleifer & Vishny,

1997). This expropriation problem by controlling shareholder is likely to be more severe to a firm's performance and might subsequently increase the likelihood of bankruptcy. This finding is consistent with Abdullah et al. (2016) who finds that controlling shareholders have a positive significant impact on predicting bankruptcy among SMEs in Malaysia. Therefore, SMEs with the presence of controlling shareholder are more likely to bankrupt.

Moreover, a significant positive coefficient is found between managing director gender (GENDER) and SME bankruptcy. GENDER is statistically significant at the 1 percent level for all the prior year to bankruptcy samples. The finding indicates that men managing director are more likely to cause bankruptcy among SMEs compared to the female counterpart. Women are believed to be more concerned with ethical behaviour than men in the workplace because they worry more about the way the company's money is spent and normally extract less personal benefits from the company than their counterpart (Barber & Odean, 2001; Bliss & Potter, 2002). Furthermore, women are more conservative than men, and therefore, are more risk averse than men. As a result, their firm risk level will be lower than firms managed by male CEOs (Vandergrift & Brown, 2005; Wei, 2007), thus reducing the probability of bankruptcy.

Moreover, women CEO would benefit the firm governance and performance through an influx of different skills, abilities, fresh perspectives and weaving of new dynamics to board deliberations (Jamali et al., 2007; Fondas & Salsalos, 2000). Women also vary in their views, values and ways to express their opinions. This would possibly result in their questioning of the conventional wisdom and open to

discussions (Huse & Solberg, 2006). The finding is similar to that of Abdullah et al. (2016) where they find that gender of managing director is positively correlated to bankruptcy among SMEs in Malaysia.

The coefficient of Malay managing director is positive and significant in predicting bankruptcy among SMEs in Malaysia compared to non-Malay managing director. The predictor is significant at the 1 percent level for all the prior to bankruptcy samples. SMEs managed by the Malays are more likely to go bankrupt compared to their non-Malay counterpart. The Malays have a high uncertainty avoidance which reflected their uneasiness in dealing with ambiguities and uncertainty (Hofstede, 1991). This suggests that the Malay managing directors would be more risk averse in doing business and their firms will have lower risk compared to others. However, with the current competitive business environment, the firms might also be losing out on business opportunities that could help the company to grow further in the future which could result in bankruptcy. Similarly, Indian managing directors are positively related to SMEs bankruptcy in Malaysia compared to foreign managing director. The predictor is significant at the 1 percent level for all the prior year to bankruptcy samples. Indian managing director is associated to business bankruptcy compared to non-Indian counterpart.

Furthermore, Chinese managing director is also positively and statistically significant with SME bankruptcy in Malaysia but only in the 2-year prior to bankruptcy sample at the 10 percent level. The Chinese are rated as low uncertainty avoidance, individualistic, willing to accept new challenges and willing to take a greater risk (Haniffa & Cooke, 2000; Hofstede, 1991). With that, SMEs managed by

the Chinese would probably face more risk in running business operation but have more opportunities in terms of growth potentials (increase market share and customer base) compared to firms manage by non-Chinese in terms of growth potentials. However, a higher risk could also lead the firm into bankruptcy.

Among the macroeconomic indicators, unemployment rate (EMPY) is the only variable that is positively significant in predicting SMEs bankruptcy in Malaysia. EMPY is statistically significant at the 10 percent level for the 3-year prior to bankruptcy sample and at the 1 percent level for the 1-year prior to bankruptcy sample. The finding shows that the higher the unemployment rate the more likely the bankruptcy of SMEs. Increase in unemployment rate generally indicates that the economy is underperforming or has a falling gross domestic product, thus more bankruptcy. Moreover, high levels of unemployment in a country may be indicative of a troubled economy with reduced consumer spending and, therefore, a reduction in business revenue. The finding is consistent with Everett and Watson (1998), Hudson, (1989) and Millington, (1994) where they also report a significant positive relationship between unemployment rate and bankruptcy. Thus, the higher the unemployment rate the more likely the SME is going to bankrupt.

4.2.3.3 Model 3: Model 1 and Model 2 Combined

The four categories of variables used in this study which include financial, non-financial, corporate governance and macroeconomic variables are combined in model 3. The results show that among the financial and non-financial variables, ROE, TLA, LQT, WCT, NWC, AGE and BLC are found to be significant in explaining business bankruptcy in both model 1 and model 3; whereas among the

corporate governance variables, MDD, CONT, NDIR, GENDER, MALAY and INDIAN are significant in predicting business bankruptcy in model 2 and model 3.

The results show a negative coefficient between profitability ratios (ROE and EBIT) and SME bankruptcy. ROE is statistically significant at the 1 percent level for the 3-year and 1-year prior to bankruptcy samples while EBIT is significant at the 1 percent level only for the 2-year prior to bankruptcy sample. Higher profitability will reduce the likelihood of SME bankruptcy, thus, hypothesis 1 is supported. Leverage ratios (TLA & CTA) are positive and statistically significant in predicting bankruptcy among SMEs in Malaysia. TLA is significant at the 1 percent level in all the prior year to bankruptcy samples while CTA are statistically significant at the 1 percent for the 2-year prior to bankruptcy sample. Hypothesis 2 is supported. This indicates that as leverage increases, firm's financial risk will rise, thus increasing its bankruptcy risk and offsetting the benefit of tax savings of debt interest. However, a negative coefficient is found between LTA and SME bankruptcy for the 2-year prior to bankruptcy sample which statistically significant at the 1 percent level.

Liquidity ratio (LQT) is negatively related to bankruptcy of SME. LQT is significant at the 10 percent level for the 3-year and 2-year prior to bankruptcy samples and at the 1 percent level for the 1-year prior to bankruptcy sample. According to hypothesis 3, lower liquidity is associated with higher probability of bankruptcy. However WCT and NWC, the other measures of SME liquidity are positive and significant predictors of bankruptcy. WCT is statistically significant at the 1 percent level for all the prior year samples while NWC is significant at the 10 percent level for the 2-year and 1-year prior to bankruptcy samples. A high WCT

and NWC show that a company is liquid and it has the ability to match its obligations on time. However, a high WCT and NWC especially for firms that are close to bankruptcy, may indicate inadequate liquidity, and therefore have to service their debt by selling their assets. This would cause a drop in the companies' total assets, thus, resulting in an increase of net working capital. This indicate a cash strapped company, selling the asset to finance day-to-day operations (Tanthanongsakkun, Pitt & Treepongkaruna, 2007).

Consistent to hypothesis 5, size (LogCAP) is found to be a positive and significantly related to SMEs bankruptcy. The variable is positive and significant at the 10 percent level for the 3-year and 2-year prior to bankruptcy samples. The bigger the size of a company, the higher is the probability of bankruptcy. It is likely that in some cases large asset based do not always imply high asset quality. For instance, a firm might have many trade debtors, but they are mostly likely to be problematic debtors with bad collection history. Other possibility might be, a firm might have a large stock of inventory that cannot be sold due to less demand.

Moreover, business location (BLC) of an SME has a negative coefficient and is significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 5 percent level for the 1-year prior to bankruptcy sample. SMEs in less industrialised states are more prone to bankruptcy. However, a positive coefficient is found between BLC and SME bankruptcy which is statistically significant at the 5 percent level for the 1-year prior to bankruptcy sample. The result show that SMEs in more industrialised states are likely to go bankrupt. This could be that SMEs located in more industrialised states are more likely to face competition from other

SMEs as well as larger corporation and multinational companies. Industrialised states attract more industry players, which makes the competition more intense in those areas (Phelps et al., 2001). Additionally, SMEs in these areas are more likely to incur more operating cost in terms of materials, labours and other operating overheads and would probably require more investments in net working capital (Watson & Everett, 1996). Therefore, hypothesis 6 is supported. In accordance to hypothesis 7, age of SME (AGE) has a negative coefficient and significant at the 1 percent level for all the prior year to bankruptcy samples. The finding indicates that younger SMEs are more prone to bankruptcy compared with older SMEs.

Duality of managing director (MDD) has a positive coefficient and significant at the 1 percent level for all the prior years to bankruptcy samples. Consistent to hypothesis 8, the presence of MDD among SME would likely lead to bankruptcy. Accordingly, advocate of agency theory argue that where the chief executive officer is the chair of the board of directors, the impartiality of the board is compromised. Accordingly, the stewardship theory is not supported by this finding. Additionally, small number of directors in SME board would increase the likelihood of bankruptcy. The results show that NDIR has a negative coefficient and statistically significant at the 1 percent level for the 3-year, 2-year and 1-year prior to bankruptcy samples. With a large number of directors on board, effective and efficient decision would be taken by the board on the on matters such as investment opportunities and business efficiency among others (Eisenberg, Sundgren, & Wells, 1998). Therefore, hypothesis 9 is supported.

Furthermore, the results show that controlling shareholder (CONT) is positive and significant predictor of SMEs bankruptcy. CONT is significant at the 10 percent level for the 3-year prior to bankruptcy sample and at the 5 percent level for the 2-year and 1-year prior to bankruptcy samples. The greater the holdings of a controlling shareholder in an SME, the likely it is to go bankrupt. Therefore, hypothesis 10 is supported. The result of independent director (IND) on SMEs bankruptcy is not as expected. The results show a significant positive relationship between IND and SMEs bankruptcy at the 5 percent level for the 3-year prior to bankruptcy sample. The presence of independent directors would lead to SMEs bankruptcy. Hypothesis 11 was not supported. Probably the executive directors are more aware and have better knowledge about the business operations and the performance of the company compared to independent directors (Raheja, 2005). This finding suggests that in the case of SMEs, the cost of having independent director could outweigh the benefit of having them on board.

Hypothesis 12 is supported. The finding shows that gender of managing director (GENDER) is having a positive and significant correlation with SME bankruptcy. GENDER is statistically significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 5 percent level for the 2-year and 1-year prior to bankruptcy samples. The finding indicates that men managing director is associated with bankruptcy compared to their female counterpart. Malay, Chinese and Indian managing directors have a positive coefficient and are significant in predicting bankruptcy among SMEs in Malaysia. INDIAN is statistically significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 5 percent level for the 2-year and 1-year prior to bankruptcy samples. MALAY and CHINESE are

statistically significant at the 1 percent level for the 3-year and 1-year prior to bankruptcy samples. SMEs managed by the Malay, Chinese and Indian are more likely to go bankrupt. Therefore, hypothesis 13 is supported.

4.2.4 Models Performance and Validation under Logistic Regression

The classification accuracy rate of a model also examines the overall model fit. The classification matrices present the level of predictive accuracy achieved by the logistic model. The predictive accuracy measure used in this study is the percentage of correctly classified cases. The values in this study are calculated for both the estimation and the holdout samples. In addition, robustness tests are performed to further assess the performance of the logistic models.

A summary of the classification rate of the models for the estimated (training) and holdout (validation) sample is provided in table 4.9. In terms of accuracy rate, the 2-year and 1-year prior to bankruptcy samples provide the highest accuracy in all the three models developed for both the training and validation samples. Model 1 has an accuracy rate of 80.6, 90 and 89 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively. The holdout sample of model 1 has an accuracy rate of 78.9, 90.4 and 89.3 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. The results show that the accuracy rate of the training and holdout sample increases by 11.7 and 14.6 percent respectively for the 2-year prior to bankruptcy sample compared with 3-year prior to bankruptcy sample. The finding also shows that model 1's accuracy rate of the estimated and holdout sample for the 2-year prior to bankruptcy sample is close to the accuracy rates reported by Abdullah et al. (2016).

Table 4.9

Logistic Regression Classification Rate for both Estimated and Holdout Sample for Malaysia

	Estimated Sample (Training)			Holdout Sample (Validation)		
	3-year	2-year	1-year	3-year	2-year	1-year
Model 1	80.6%	90%	89%	78.9%	90.4%	89.3%
Model 2	72.3%	77.4%	77.2%	72.9%	78.7%	77.4%
Model 3	84.3%	93.4%	91.4%	82.7%	92.5%	83.4%
N	534	376	336	132	94	84

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. N Represents number of observation in the analysis.

Similarly, the accuracy rate of model 2 for the estimated and holdout sample increases by 7 and 8 percent for the 2-year prior to bankruptcy compared to the accuracy rate reported for the 3-year prior to bankruptcy sample. Model 2 accuracy rate of the training sample is 72.3, 77.4 and 77.2 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. The results of the holdout sample for the model is 72.9, 78.7 and 77.4 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively. Additionally, model 3 provides the highest predictive accuracy rate for both estimated and holdout sample as the model combined the financial, non-financial, corporate governance and macroeconomic variables. The accuracy rate of the estimated sample is 84.3, 93.4 and 91.4 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively. The results also show a similar trend where the accuracy rate of the training and holdout sample increase by 10.8 and 11.9 percent respectively for the 2-year prior to bankruptcy sample compared with 3-year prior to bankruptcy sample.

The overall finding of the accuracy rate for both the training and holdout samples show that the models predict bankruptcy more accurate as we move closer to bankruptcy especially in the 2-year prior to bankruptcy sample. This may be due to

the deteriorating financial stability of a firm progressively in terms of profitability, liquidity and other factors due to the adverse effect of the litigation process which might divert the management attention. The finding is consistent with the conclusion made by Abdullah et al. (2016) that models with a period closer to the business failure predict better compared with models far away from the failure events.

4.3.4.1 Robustness Check on the Classification Accuracy of the Logistic Regression Models

To further check the robustness of the models performance, the receiver operating characteristic (ROC) is utilised. The area under the ROC curve is used to check and validate the robustness of the predictive accuracy of the models' estimates (Bauer & Agarwal, 2014). ROC curve is a graphical plot which illustrates the performance of a binary classifier system. It is created by plotting the fraction of true positives out of the positives (TPR = true positive rate) versus the fraction of false positives out of the negatives (FPR = false positive rate) at various threshold settings. TPR is also known as sensitivity while FPR is one minus the specificity or true negative rate. For comparison across models, the area under the ROC curve is usually measured relative to the area of the unit square. A value of 0.5 indicates a random model with no predictive ability, and a value of 1.0 indicates perfect discrimination (Hosmer et al., 2013).

Table 4.10

ROC Classification Rate for Malaysia Models

Models	3-year Prior Sample	2-year Prior Sample	1-year Prior Sample
Model 1	88.8%	96.8%	94.8%
Model 2	78.3%	82.7%	84.0%
Model 3	92.1%	98.4%	97.3%
N	534	376	336

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. N Represents number of observation in the analysis.

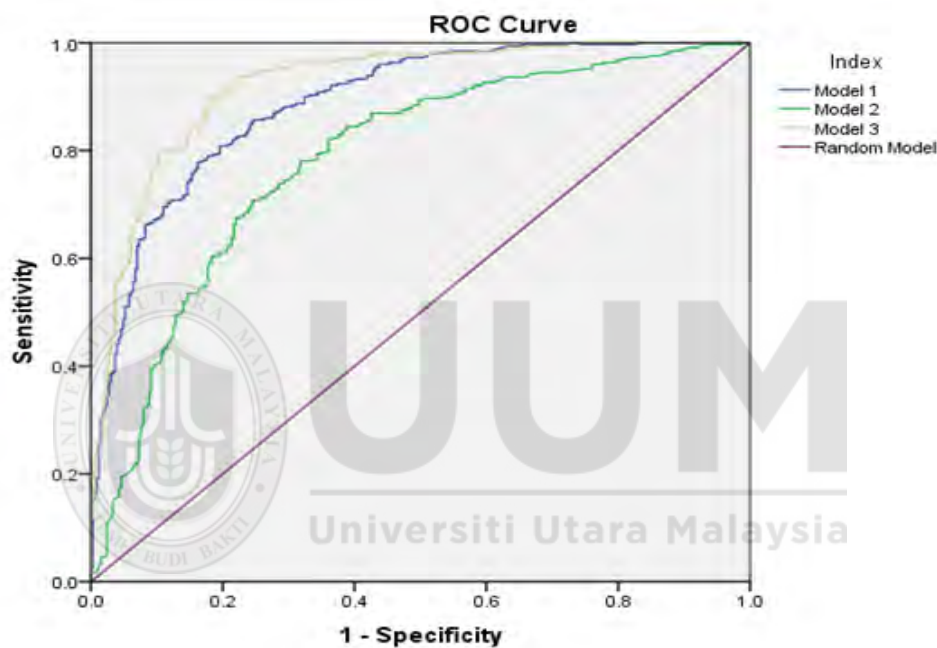


Figure 4.1

Comparison of ROC curves between models developed using 3-year prior sample

The ROC curves for models 1, model 2 and model 3 using 3-year prior sample is graphically presented in Figure 4.1. Table 4.10 provides the area under the curve (AUC) score for each model under the prior year's to bankruptcy samples. Consistent to the logistic regression accuracy rates, the results of the ROC curve show that the accuracy rate of the models increases as we move closer to bankruptcy. For the 3-year prior to bankruptcy sample, Model 1 and model 3 with a respective AUC of 0.888 and 0.921 predict bankruptcy better than model 2 (with

0.783). Furthermore, the AUC of model 3 that incorporates financial, non-financial, governance and macroeconomic variables increases about 3.7 percent (92.1-88.8/88.8) from model 1 AUC, suggesting that model 3 has a superior performance.

Furthermore, the AUC scores for the 2-year and 1-year prior to bankruptcy samples show that model 3 which incorporates all variables has a larger area under the ROC curve compared with model 1 and model 2 as graphically presented in figure 4.2 and 4.3. For the 2-year prior to bankruptcy sample, the AUC of model 3 improves with about 1.7 percent (98.4/96.8) compared to model 1. Similarly, the AUC of model 3 increases by 2.6 percent (97.3/94.8) compared to model 1 for the 1-year prior to bankruptcy sample. An observed improvement of the performance of model 2 is also observed for the 2-year and 1-year prior to bankruptcy samples as compare to the 3-year prior to bankruptcy sample. This indicates that as we move closer to bankruptcy, the effect of corporate governance and macroeconomic variables in model 2 become more important. Among all the models, model 3 is the best model as it has the highest area under the curve for all the three years prior to bankruptcy samples and model 3 of the 2-year prior to bankruptcy sample is having the highest area under the curve of 98.4 percent.

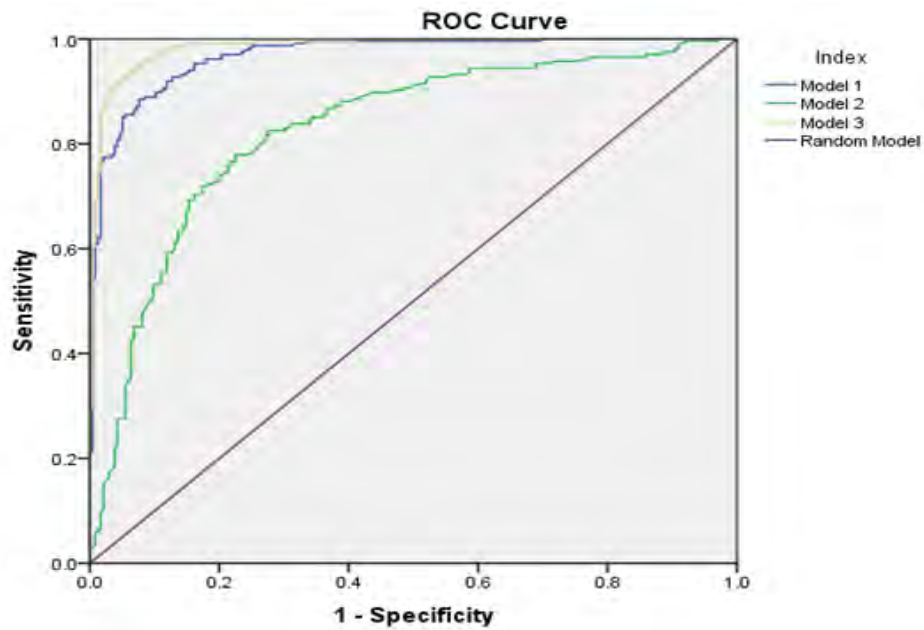


Figure 4.2
Comparison of ROC curves between models developed using 2-year prior sample

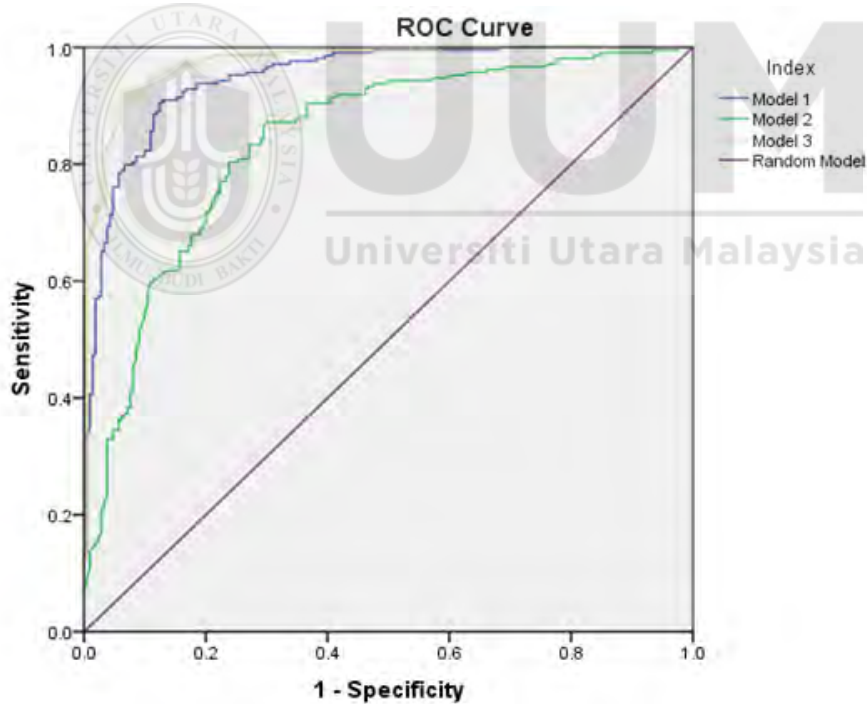


Figure 4.3
Comparison of ROC curves between models developed using 1-year prior sample

Additionally, the study employs the Brier score to assess the prediction accuracy of the models. The Brier Score (BS) is a commonly used measure for evaluating

probabilistic forecasts (Roulston, 2007). Brier score is a score function that measures the accuracy of probabilistic predictions. It compares predicted probabilities with observed binary responses. The Brier score is appropriate for binary and categorical outcomes that take the value as true or false, but is inappropriate for ordinal variables which take on three or more values. This is because the Brier score assumes that all possible outcomes are equivalently "distant" from one another.

This function returns a score of the mean square difference between the actual outcome and the predicted probability of the possible outcome. The actual outcome has to be 1 or 0 (true or false), while the predicted probability of the actual outcome can be a value between 0 and 1. The Brier score loss is also between 0 to 1, and the lower the score (the mean square difference is smaller), the more accurate the prediction will be.

$$BS = \frac{1}{N} \sum_{t=1}^N (f_t - O_t)^2 \quad (20)$$

Where

N is the total number of predictions,

f_t is the probability that was forecasted and

O_t the actual outcome of the event (0 if it does not happen and 1 if it does happen).

The Brier score for a model can range from 0 for a perfect model to 0.25 for a non-informative model with a 50% incidence of the outcome. When the outcome incidence is lower, the maximum score for a non-informative model is lower.

Table 4.11

Brier Score for Malaysian Models

Models	3-year Prior Sample	2-year Prior Sample	1-year Prior Sample
Model 1	0.1333	0.0701	0.0881
Model 2	0.1889	0.1696	0.1620
Model 3	0.1100	0.0453	0.0602
N	534	376	336

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2.

Looking at table 4.11, consistent with what has been found earlier (classification rate and ROC), the Brier Score of the models developed decreases as the bankruptcy approaches (between 3-year prior and 2-year prior to bankruptcy sample). However, the score increase in 1-year prior sample compared to 2-year prior to bankruptcy sample. The 2-year prior to bankruptcy sample has the lowest score compared to other samples. Furthermore, model 3 that incorporate the financial, non-financial, corporate governance and macroeconomic predictors performs better in all the prior to bankruptcy year samples. Model 3 Brier score for 3-year prior to bankruptcy sample is 0.11, 0.0453 for 2-year prior to bankruptcy sample and 0.0602 for the 1-year prior to bankruptcy sample. The best model identified using this approach is again model 3 for the 2-year prior to bankruptcy samples as it carries the lowest score of 0.0453.

4.2.5 Endogeneity Test

In this section, the study addresses the challenges posed by the finding of Miglani et al. (2015) and Schultz et al. (2015), that the relationship between corporate governance measures and bankruptcy is spurious due to endogeneity bias. Therefore, it is important that endogeneity is taken into account as the presence of unobserved influences is likely to generate a degree of correlation between

regressors' and the error terms, which leads to biased estimates of the regressors' coefficients. To address whether bankruptcy and corporate governance indicators may suffer from the endogeneity problem, 2 stage least square (2SLS) regression is used to perform a more robust analysis on the affected corporate governance variables (i.e. NDIR, IND and MDD) for model 2 and model 3²³. This method requires an instrumental variable (IV) that is correlated with the corporate governance indicators, but does not affect bankruptcy.

The study used industry-average number of directors (IND_NDIR) as the IV for NDIR, industry-average proportion of independent directors (IND_IND) as the IV for IND, average percentage of shares owned by directors (DIR%Own) as IV for MDD and proportion of firm's tangible assets (TNGASSET) as an instrument in order to run the Hansen-Sargen test statistic for over-identification. Under the 2SLS regression, the Durbin-Wu-Hausman test is performed on the selected variables to test if the residual values of NDIR, MDD and IND are jointly equal to zero. If the F-statistic is significant, then the null hypothesis is rejected, suggesting that the variables are not exogenous and that endogeneity is present.

Table 4.12 presents the results of the endogeneity test for model 2. The finding shows that the instrumental variables used to run the endogeneity test are suitable based on the significance of the F-statistics of the first-stage regression and Hansen-Sargen test statistic for over-identification. The Hansen-Sargen test is statistical insignificant for NDIR. For the 3-year prior to bankruptcy sample, the test is Sargan (score) $\chi^2(1) = 0.1403$, p-value = 0.7080, the test for 2-year prior to bankruptcy

²³ Model 1 is excluded in the analysis because it does not included corporate governance variables.

sample is Sargan (score) $\chi^2(1) = 0.3365$, p-value = 0.5619 and for 1-year prior to bankruptcy sample the test is Sargan (score) $\chi^2(1) = 0.0096$, p-value = 0.9233. Moreover, The Hansen-Sargen test for MDD is Sargan (score) $\chi^2(1) = 1.4851$, p-value = 0.2230 for 3-year prior sample, Sargan (score) $\chi^2(1) = 0.2246$, p-value = 0.6356 for 2-year prior sample and Sargan (score) $\chi^2(1) = 0.3224$, p-value = 0.5701) for the 1-year prior to bankruptcy sample. The Hansen-Sargen test indicates that the instrumental variables sets are valid (Stock & Yogo, 2005).

Furthermore, from table 4.12, the Durbin-Wu-Hausman test shows that the F-statistic of number of directors (NDIR) for the 2-year prior to bankruptcy sample (F-statistic = 3.8364, p-value = 0.048) and for the 1-year prior to bankruptcy sample (F-statistic = 23.103, p-value = 0.006) are significant, which confirm the presence of endogeneity. Similarly, the Durbin-Wu-Hausman test results show that the F-statistics of the managing director duality (MDD) for the 1-year prior to bankruptcy sample (F-statistic = 4.5193, p-value = 0.032) is statistically significant, which confirm the presence of endogeneity. With the presence of endogeneity problem, these variables will require 2SLS regression.

Table 4.12

The results of endogeneity test for Model 2 using Instrumental Variable Approach Malaysia Sample

Variables	3-Year Prior to Bankruptcy Sample		2-Year Prior to Bankruptcy Sample			1-Year Prior to Bankruptcy Sample		
	First Stage NDIR	First Stage MDD	First Stage NDIR	First Stage MDD	Second Stage Logistic Regression	First Stage NDIR	First Stage MDD	Second Stage Logistic Regression
Constant	2.8310***	-0.0419	3.3420***	0.0926	6.5654*	2.9549***	0.1936*	10.790***
GDP	-0.0117	0.0131**	-0.0288	-0.0047	0.1219**	-0.0154	0.0184**	0.2139***
LNR	0.6910	-0.0891	0.7844	0.2576		-1.2198	-0.0850	
CPI	-0.0184	0.0090	-0.0802	-0.0277	0.8440***	-0.8839	0.0336	0.5751***
EMPY	-0.1781	-0.2651	-0.6381	0.5824*	21.89***	-0.9429*	0.0662	
GENDER	-0.3184***	0.0828**	-0.2854***	0.0445	0.8984**	-0.1495	0.1432***	1.5489**
CONT	0.0081	0.2618***	0.0243	0.2346***	6.0130***	0.0537	0.1317***	0.8850**
NDIR		-0.0228*		-0.0299*	-3.1989***		-0.0506***	-4.4819***
IND	0.2901***	-0.3326***	0.3035**	-0.2507***	8.6586***	0.2821**	-0.2781***	5.7667***
MDD	-0.1591*		-0.2356*		29.706***	-0.3411***		14.276***
CHINESE	-0.2893***	0.1862***	-0.4272***	0.0883*	-3.2603***	-0.3199*	0.1640**	-2.9986***
MALAY	0.0752	0.2039***	-0.4216***	0.0721	-2.2099***	-0.1526	0.1718**	-1.6982***
INDIAN	-0.0619	0.0466	-0.1283	-0.0627	3.0688***	-0.0791	-0.0620	2.0552***
DIR%Own		0.0559**		0.0478**			-0.1351**	
IND_NDIR	0.0497*		-0.0359***			0.0115*		
R-squared	0.0805	0.1956	0.0806	0.1572		0.0782	0.1840	
F-value	4.70	13.05	3.34	7.10		2.87	7.63	
	(0.000)***	(0.000)***	(0.001)***	(0.000)***		(0.001)***	(0.000)***	
Durbin-Wu-Hausman	0.0547	0.1232	3.8364	0.3694		23.103	4.5193	
	(0.8150)	(0.7256)	(0.0477)**	(0.5436)		(0.0056)***	(0.0315)**	
Hansen-Sargan test	0.1403	1.4851	0.3365	0.2246		0.0096	0.3224	
	(0.7080)	(0.2230)	(0.5619)	(0.6356)		(0.9233)	(0.5701)	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (FOREIGN), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY), industry-average number of directors (IND_NDIR), average percentage of shares owned by directors (DIR%Own).

Table 4.13

The results of endogeneity test for Model 3 using Instrumental Variable Approach Malaysia Sample

Variables	1-Year Prior to Bankruptcy Sample		Second Stage Logistic Regression
	First Stage Reg NDIR	First Stage Reg MDD	
Constant	2.7375***	0.3735**	14.639***
NDIR		-0.0424**	-6.5741***
MDD	-0.2752**		13.979***
EBIT	0.1410	0.0018	
ROE	0.0362	-0.0097	-0.2405*
TLA	-0.1052	0.0155	0.3037**
LTA	0.0339	-0.0248	
CTA	-0.0310	-0.0231	
CLE	0.0078	0.0160	
LQT	0.0528	-0.0191	-0.5255**
WCT	-0.1210*	0.0362	
NWC	7.83e-09	1.6e-09	
AST	0.1879***	-0.0250	-1.0189*
EXP	-0.1715	-0.0649	-1.1269*
LogTA	-0.0277	-0.0099	
LogCAP	0.0374**	0.0084	
AGE	0.0395	-0.0077	-0.0906***
BLC	0.0581	-0.0130	-0.4911**
GENDER	-0.0232	0.1175**	
IND	0.3366**	-0.2811***	6.3219***
CONT	0.0855	0.1187***	0.1715**
CPI	-0.1021	0.0326	-0.8254**
GDP	-0.0144	0.0153*	
LNR	-0.8256	-0.1323	
EMPY	-0.4921	0.0473	3.5544***
CHINESE	-0.2370	0.1578**	-2.5615***
MALAY	-0.0352	0.1705**	
INDIAN	-0.0033	-0.0780	3.9731***
DIR%Own		-0.1308***	
IND_NDIR	-0.0190**		
R-squared	0.1665	0.2183	
F-value	2.89 (0.000)***	4.04 (0.000)***	
Durbin-Wu-Hausman	17.1438 (0.000)**	2.7696 (0.0890)*	
Hansen-Sargan test	0.02644 (0.9590)	0.7414 (0.3892)	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Indian (INDIAN), ethnicity of managing director as Malay (MALAY), ethnicity of managing director as Chinese (CHINESE), ethnicity of managing director as Foreign (Foreign), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY), industry-average number of directors (IND_NDIR), average percentage of shares owned by directors (DIR%Own).

However, the results in table 4.12 of the Durbin-Wu-Hausman test for model 2 show that MDD and NDIR are insignificant for the 3-year prior to bankruptcy samples. The F-statistic is 0.1233 (p-value = 0.726) for MDD and 0.0548 (p-value = 0.815) for NDIR. Similarly, the F-statistic of the Durbin-Wu-Hausman test of MDD for the 2-year prior bankruptcy sample is statistically insignificant. These findings suggest that there is no indication of endogeneity for the variables in the respective prior year to bankruptcy samples. Moreover, IND is an insignificant variable in the main analysis (logistic regression) for all the prior year samples for model 2. Therefore, the variables may not require the 2SLS regression as suggested by Baum, Schaffer and Stillman (2003). In summary, the results estimated using the logistic regression in the main analysis is robust due to the absence of endogeneity.

Table 4.14
Durbin-Wu-Hausman test and Hansen-Sargen test for model 3 Malaysian sample

	Model 3				
	3-Year Prior Sample			2-Year Prior Sample	
	NDIR	MDD	IND	NDR	MDD
Durbin-Wu-Hausman test	0.4878 (p=0.4852)	0.3954 (p=0.5297)	0.0585 (p=0.8089)	0.9693 (p=0.2591)	0.0753 (p=0.7839)
Hansen-Sargen test	0.0382 (p=0.8450)	0.3882 (p=0.5332)	0.0335 (p=0.8547)	0.1071 (p=0.7435)	0.6422 (p=0.4229)

Note: Numbers in parentheses represents the respective p-values

Moreover, table 4.13 presents the results of the endogeneity test for model 3 using the 2SLS. The finding show that only NDIR and MDD for the 1-year prior to bankruptcy sample are affected. The results from the Durbin-Wu-Hausman test show that the F-statistic of NDIR (F-statistic = 17.1438, p-value = 0.000) and MDD (F-statistic = 2.7696, p-value = 0.089) are significant, which confirm the presence of endogeneity. However, NDIR, MDD and IND for 3-year and 2-year prior to bankruptcy samples are not affected as such do not require endogeneity test as presented in table 4.14.

Overall, the Durbin-Wu-Hausman test (table 4.12 and 4.13) compares the logistic regression and 2SLS model coefficients. The null hypotheses is that the regressors are exogenous is rejected. Therefore, NDIR and MDD are endogenous regressors and the coefficients on the second stage of the 2SLS are more robust, appropriate and unbiased estimate to use. The results of the endogenous variables (NDIR and MDD) in table 4.12 and 4.13 using the 2SLS regression shows that the number of directors (NDIR) is negative and significant predictor of bankruptcy at the 1 percent level for 2-year and 1-year prior to bankruptcy sample in model 2 and also at the 1 percent level in model 3 for 1-year prior to bankruptcy sample. Increase in board size reduces the probability of bankruptcy among SMEs. Thus, it can be stated that larger board can decrease the probability of SMEs bankruptcy.

Similarly, managing director duality (MDD) is positive and significant predictor of SME bankruptcy at the 1 percent level for 2-year and 1-year prior to bankruptcy sample in model 2 and also at the 1 percent level in model 3 for 1-year prior to bankruptcy sample. The presence of managing director duality increases the probability of bankruptcy. CEO-duality may likely leads to more controlling, lower levels of control and over-concentration of decision-making functions. This is consistent with the inference that is made from the main finding using logistic regression.

Generally, the findings show that there is presence of endogeneity problem among NDIR and MDD for the 2-year and 1-year prior to bankruptcy samples in model 2 and 1-year prior to bankruptcy sample for model 3. The presence of endogeneity

problem on these variables (NDIR and MDD) suggest that changes in business failure status of SME also has an influence on the corporate governance of the firm.

4.2.6 Artificial Neural Network Analysis of Malaysian Sample

The artificial neural network (ANN) used in this study is the multilayer perceptron (MLP) which is a feed-forward network composed of input-hidden-output layers. The three-layer MLP is selected for this study because it is the commonly used ANN architecture for prediction and two-group classification problem such as the problem in this study (Charitou et al., 2004; Zhang et al., 1999).

Table 4.15 presents the ANN results for the 3-year, 2-year and 1-year prior to bankruptcy samples. The models performances are measured using mean square error (MSE) and sum of square error (SSE). MSE and SSE objective is to minimise the average of the sum of errors in the weight matrices where a value closer to 0 indicates that the model has a minimised or smaller random error component, and that the model is fit and would be useful for prediction.

Results show that model 3 that incorporates financial, non-financial, corporate governance and macroeconomic variables has the least error and performs better compared to model 1 and model 2 based MSE and SSE. Model 3 has the least error using MSE compared to model 1 and model 2 with an error score of 0.116, 0.082 and 0.165 for the 3-year, 2-year and 1-year prior to bankruptcy samples, respectively. Model 1 scores the least error using MSE for the 1-year prior to bankruptcy sample with 0.11 compared to model 2 (0.166) and model 3 (0.165). More so, as we move closer to bankruptcy, model 1 and model 2 error reduce.

Table 4.15

Artificial Neural Network of Malaysian Sample

Variables	Model 1			Model 2			Model 3		
	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior
	Weight	Weight	Weight	Weight	Weight	Weight	Weight	Weight	Weight
Bias	-0.491	-2.164	-5.059	-3.588	0.426	-0.799	-0.877	1.587	-2.452
EBIT		6.543	-1.415					-6.891	-3.568
ROE	0.936	0.864	-9.064				2.311	-1.264	-7.464
TLA	-2.438	-3.670					-5.809	8.900	
CTA		-2.974	2.172				1.022	3.140	1.447
CLE		-0.971							2.243
LQT	1.006	0.845	-7.747				2.167	-2.571	-7.673
WCT		0.588						1.859	
NWC	1.196		2.160				-0.271	-0.629	-0.158
EXP	-0.769							0.724	-3.158
AST			17.394				1.500	0.629	-6.896
LogCAP	-0.501								
LogTA			2.735				-3.203	1.335	2.202
AGE	3.434	1.942	-5.788				13.024	-5.080	-4.346
BLC									
MDD				-6.483		-1.218			
CONT				-4.173	-1.162	-0.843	-0.093		
NDIR				8.133	3.418	2.177	3.179	-2.550	
GENDER				-4.587	-1.617	-0.688	-3.916		
MALAY				-4.867	-1.408	-1.156	4.168		
INDIAN				-3.630	1.423	-0.789	-4.241		
CHINESE					0.871	-0.790			
EMPY						-0.600	-1.630	-0.962	
GDP					-0.763	-0.299			
LNR						-0.473			
No. Hidden Layer	1	1	1	1	1	1	1	1	1
SSE	68.921	23.609	25.346	97.222	56.282	47.524	49.904	10.773	13.084
MSE	0.136	0.141	0.111	0.186	0.171	0.166	0.116	0.082	0.165

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Malay (Malay), ethnicity of managing director as Chinese (Chinese), ethnicity of managing director as Indian (Indian), ethnicity of managing director as Foreign (Foreign), gross domestic product (GDP), lending rate (LNR), consumer price index (CPI) and unemployment rate (EMPY). Sum of square Error (SSE), Mean Square Error (MSE).

Using the Neural Interpretation Diagram (NID)²⁴ and Garson's algorithm²⁵ methods which allow the researcher to qualitatively examine the importance of the explanatory variables given their relative influence on response variables, the most important variables were identified. Similar to the logistic regression results, profitability (ROE), liquidity (LQT) and the age of the company (AGE) appeared in model 1 and model 3 in all the prior year to bankruptcy samples. The leverage (TLA), expense (EXP), net working capital ratio (NWC), size (LogCAP) and asset turnover (AST) also appeared in both models but not in all the prior year's to bankruptcy samples. Furthermore, the gender of managing director (GENDER), controlling shareholders (CONT), number of directors (NDIR), ethnicity of managing director (MALAY and INDIAN) and unemployment rate (EMPY) also appeared in model 2 and model 3 but not in all the prior year to bankruptcy samples. The results show the significant of these variables in predicting bankruptcy among SMEs in Malaysia using ANN. However, managing director duality (MDD), Chinese managing director (CHINESE), percentage change in GDP and LNR appear only in model 2. Correspondingly, these variables are also significant predictors using logistic regression.

²⁴ Refer to Appendix 3 to visualize the diagrams.

²⁵ Refer to Appendix 3 to visualize the diagrams.

4.2.7 Models Performance and Validation under ANN

Table 4.16 provides a summary of the classification rate of the models for the estimated and holdout sample. Model 1 has an accuracy rate of 82.9, 92.3 and 91.9 percent for 3-year, 2-year and 1-year prior to bankruptcy samples respectively. The holdout sample for model 1 is having an accuracy rate of 76.1, 90.7 and 88.2 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. Furthermore, model 2 accuracy rate of the estimated sample is 74.8, 79.5 and 80.6 percent for the respective 3-year, 2-year and 1-year prior bankruptcy samples. The holdout sample for model 2 has an accuracy rate of 73.6, 73.3 and 67.9 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples.

In addition, model 3 that combined both financial, non-financial, corporate governance and macroeconomic variables provides the highest predictive accuracy rate both for the estimated and holdout sample except for the holdout sample of 1-year prior to bankruptcy sample. The accuracy rate of the estimated (holdout) sample is 89.7(83.5%), 97.6(91.1%) and 96.0(81.7%) percent for 3-year, 2-year and 1-year prior to bankruptcy respectively.

Table 4.16

ANN Classification rate for both estimated and holdout sample for Malaysia

	Estimated Sample (Training)			Holdout Sample (Validation)		
	3-year	2-year	1-year	3-year	2-year	1-year
Model 1	82.9%	92.3%	91.9%	76.1%	90.7%	88.2%
Model 2	74.8%	79.5%	80.6%	73.6%	73.3%	67.9%
Model 3	89.7%	97.6%	96.0%	83.5%	91.1%	81.7%
<i>N</i>	534	376	336	132	94	84

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. *N* represents number of SMEs in the analysis.

4.2.8 Comparison of the Accuracy Rate between Logistic Regression and ANN

The comparison is performed based on the type I error and type II error. Type I error refers to the classification of bankrupt SMEs as non-bankrupt; whereas type II error refers to the classification of non-bankrupt SMEs as bankrupt.

In tables 4.17, ANN models shows the lowest errors rate in both type I and type II in all the models compared to logit models except for model 1 type II error on the 3-year (19.2% v 21.0%) and 2-year (10.3% v 8.9%) prior to bankruptcy samples. ANN model 2 also type I error misclassified bankrupt SMEs poorly than that of the logit model for the 2-year (17.4% v 18.8%) prior to bankruptcy sample. Business bankruptcy prediction of model 3 using ANN method provides a consistently lower type I and type II error than the logistic regression method for all the prior year samples. Considering that the type I error refers to the misclassification of bankrupt firms (which is also consider to be costly compared to type II error), this feature of the ANN method can be considered as advantageous indicating a higher ability of the method to identify bankrupt firms. Overall, the type II error is considerably higher than the type I error for all the models throughout the prior year samples.

On the overall accuracy rate, ANN models provide the highest percentages for the estimated sample for all prior year samples as presented in table 4.16. ANNs is more robust than the logistic model where results of model 1 for all prior year to bankruptcy samples show a higher accuracy rate (for 3-year prior sample, 82.9% vs 80.6%; for 2-year prior sample, 92.3% vs 90% and 1-year prior to bankruptcy samples, 91.9% vs 89%). Similarly, ANN outperforms the logit model for all prior

year samples of model 2 where the result is 74.8 versus 72.3 percent for 3-year prior to bankruptcy sample, 79.5 versus 77.4 percent for 2-year prior sample and 80.6 versus 77.2 percent for 1-year prior to bankruptcy sample.

Table 4.17

Misclassification rates of the different models for Malaysia

	Type I error rate			Type II error rate		
	3-Year	2-year	1-Year	3-Year	2-year	1-Year
Logistic Regression Approach						
Model 1	19.5%	11.1%	9.0%	19.2%	8.9%	12.9%
Model 2	27.8%	17.4	23%	27.7%	27.7%	22.9%
Model 3	15.6%	7.2%	8.1%	15.8%	6.0%	9.0%
Artificial Neural Network Approach						
Model 1	13.2%	5.3%	7.4%	21.0%	10.3%	8.7%
Model 2	19.0%	18.8%	17%	31.8%	22.3%	21.6%
Model 3	6.4%	3.2%	3.6%	14.4%	1.7%	4.4%

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. The overall misclassification error is estimated as the average of the type I and the type II error rates.

Moreover, the result from model 3 further shows the superior of ANN model compared to the logit model in estimating the overall classification rate across the estimated samples. This is evident from the accuracy rate for 3-year prior to bankruptcy sample (89.7% vs 84.3%), 2-year prior to bankruptcy sample (97.6% vs 93.4%) and 1-year prior to bankruptcy sample (96% vs 91.4%). In brief, comparing type I error rate and type II error rate as well as the overall accuracy rate of the bankruptcy prediction models developed in this study, a conclusion can be made that ANN model is better in predicting SMEs bankruptcy in Malaysia (Ciampi et al., 2009; Neophytou et al., 2001; Park, 2005; Shin & Lee, 2002; Zhang et al., 1999).

However, accuracy rate of logistic regression is higher for the holdout sample compared with ANN. The accuracy rate of the holdout sample for model 1 is 89.3 percent versus 88.2 percent for the 1-year prior to bankruptcy sample and 78.9 percent versus 76.1 percent for the 3-year prior to bankruptcy sample. Similarly, the holdout sample accuracy rate for logit model for model 2 is higher compared to ANN where the result is 78.7 versus 73.3 percent for the 2-year prior to bankruptcy sample and 77.4 versus 67.9 percent for the 1-year prior to bankruptcy sample. A similar trend is found in model 3 where the accuracy rate of the holdout sample for logit model is higher than ANN. This is evident from the accuracy rate for the 2-year prior to bankruptcy sample (92.5% vs 91.1%) and the 1-year prior to bankruptcy sample (83.4% vs 81.7%).

4.2.9 Summary of the hypothesis of Malaysian Sample

The objective of this study is to develop bankruptcy prediction models among SMEs using financial, non-financial, corporate governance and macroeconomic variables. The finding were presented in the previous sections and the summary of the relations found between each of the independent variables and bankruptcy of SMEs in Malaysia are as follows:

Table 4.18

The summary of the hypothesis and the finding – the relationship between the financial, non-financial, corporate governance and macroeconomic indicators and SMEs bankruptcy.

Hypotheses	H. Sign	A. Sign	Sig.	Conclusion
<i>H1: There is a negative relationship between profitability and bankruptcy.</i>	-	-	Sig. (5%)	Supported
<i>H2: There is a positive relationship between leverage and bankruptcy.</i>	+	+	Sig. (5%)	Supported
<i>H3: There is a negative relationship between liquidity and bankruptcy.</i>	-	-	Sig. (5%)	Supported
<i>H4a: There is a negative relationship between activity ratios (asset turnover) and bankruptcy.</i>	-	-	Sig. (5%)	Supported
<i>H4b: There is a positive relationship between activity ratio (expense ratio) and bankruptcy.</i>	+	+		Not Supported
<i>H5: There is a relationship between size of SME and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H6: There is a relationship between business location and bankruptcy.</i>	+/-	-	Sig. (5%)	Supported
<i>H7: There is a negative relationship between age of SME and bankruptcy.</i>	-/+	-	Sig. (5%)	Supported
<i>H8: There is a relationship between CEO duality and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H9: There is a relationship between board size and bankruptcy.</i>	+/-	-	Sig. (5%)	Supported
<i>H10: There is a relationship between controlling shareholder and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H11: There is a negative relationship between independent director and bankruptcy.</i>	-	+	Sig. (5%)	Not Supported
<i>H12: There is a relationship between gender of managing director and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H13: There is a relationship between ethnicity of managing director (MALAY, CHINESE and INDIAN) and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported

<i>H14: There is a negative relationship between GDP and bankruptcy.</i>	-	-	Not supported
<i>H15: There is a positive relationship between unemployment and bankruptcy.</i>	+	+	Not Supported
<i>H16: There is a positive relationship between inflation rate and bankruptcy.</i>	+	+	Not Supported
<i>H17: There is a positive relationship between interest rate and bankruptcy.</i>	+	+	Not supported

Note: H= Hypothesised, A= Actual, Sig.= Significance

4.3 Nigerian SMEs

The second country analysis is on the Nigeria SMEs (1-year, 2-year and 3-year prior to bankruptcy samples). The objective is to predict bankruptcy using financial, non-financial, corporate governance and macroeconomic variables using logistic regression and ANN. The analysis compared the predictive accuracy rate of models developed as well as the method that provides the highest rate.

4.3.1 Descriptive Statistics of Nigerian Sample

Table 4.19 to 21 report the summary statistics of all independent variables for both bankrupt and non-bankrupt SMEs. Mean difference test is conducted between the bankrupt and non-bankrupt SMEs for all the samples is conducted. In general, the findings are in line with the expectation of the study. There are significant differences in the characteristics between the bankrupt and non-bankrupt SMEs. The variables ROE, TLA, LTA, CLA, CLE, LQT, WCT, AGE, IND, NDIR and GENDER are significantly difference at the 1 percent level as presented in table 4.19 (3-year prior to bankruptcy sample). Furthermore, the variables BLC, HAUSA and YARUBA are significantly different at the 5 percent level while EXP and LogCAP are significantly different at the 10 percent level. However, some of the

variables such as EBIT, NWC, AST, LogCAP, CONT, MDD, IGBO and FOREIGN are insignificant.

Additionally, the univariate analysis for the 2-year prior to bankruptcy sample (table 4.20) shows that the variables ROE, EBIT, CLA, WCT, EXP, BLC, CONT, MDD and GENDER are significantly different at the 1 percent level between the bankrupt and non-bankrupt SMEs. However, variables such as NWC, AGE and NDIR are significantly different at the 5 percent level while TLA is significantly different at the 10 percent level. For the 1-year prior to bankruptcy sample the univariate analysis shows that the variables EBIT, AST, EXP, AGE and CONT are significantly different at the 1 percent level between both groups (table 4.21). The variables such as ROE, NWC, BLC, MDD and HAUSA are significantly different at the 5 percent level while TLA and CLE are significantly different at the 10 percent level between the bankrupt and non-bankrupt SMEs.

Overall, mean comparison between the two groups suggests that SMEs in the bankrupt group are less profitable compared to non-bankrupt SMEs in all the three year prior samples (1, 2 and 3-year prior to bankruptcy sample). As bankruptcy approaches, the profitability of the bankrupt companies' decreases as presented in table 4.19 to 21. This finding is similar to what has been found on Malaysian SMEs by Abdullah et al. (2016). In addition, lower liquidity (LQT and WCT), high operational cost (EXP) and lower assets turnover (AST) further could contribute to the negatives profits for the bankrupt SMEs in the 2-year and 1-year prior to bankruptcy samples.

Table 4.19
Descriptive Statistics of Nigeria Sample

3 year prior to bankruptcy sample					
Variables	Bankrupt SMEs		Non-bankrupt SMEs		t-test
	Mean	St. D	Mean	St. D	
ROE	0.745	0.267	2.487	0.185	0.00***
EBIT	0.867	0.234	1.158	0.318	0.607
TLA	0.898	1.129	0.440	0.349	0.00***
LTA	0.659	0.458	0.147	0.235	0.00***
CLA	0.742	0.501	0.397	0.611	0.00***
CLE	0.508	0.516	0.125	0.576	0.00***
LQT	0.577	0.412	2.378	1.054	0.00***
WCT	0.578	0.298	0.903	0.643	0.00***
NWC	2282	0.599	2350	264.7	0.949
AST	0.802	1.032	0.728	0.649	0.786
EXP	0.697	0.583	0.455	0.268	0.08*
LogTA	14.18	2.295	12.74	2.984	0.364
LogCAP	15.09	1.835	15.46	2.089	0.061*
AGE	15.76	7.855	25.37	10.53	0.01***
BLC	0.366	0.486	0.678	0.468	0.026**
IND	0.129	0.199	0.319	0.264	0.00***
NDIR	2.761	1.509	4.818	2.195	0.01***
CONT	0.825	0.385	0.543	0.499	0.507
MDD	0.401	0.491	0.368	0.483	0.189
GENDER	0.901	0.299	0.801	0.402	0.00***
HAUSA	0.226	0.419	0.287	0.457	0.026**
YARоба	0.319	0.467	0.198	0.402	0.01**
IGBO	0.267	0.443	0.263	0.446	0.808
FOREIGN	0.186	0.392	0.257	0.438	0.120
N	172	172	171	171	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yoroba (YARоба), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN). Number of observation (N)

Table 4.20

Descriptive Statistics of Nigeria Sample

Variables	2 year prior to bankruptcy sample				
	Bankrupt SMEs		Non-bankrupt SMEs		t-test
	Mean	St. D	Mean	St. D	
ROE	-0.795	1.908	0.089	2.188	0.00***
EBIT	-0.269	0.594	0.023	0.141	0.01***
TLA	1.6396	1.698	1.069	1.707	0.095*
LTA	0.081	0.314	0.058	0.235	0.262
CLA	0.932	0.129	0.867	0.184	0.001***
CLE	0.289	0.403	0.147	0.784	0.110
LQT	1.583	5.414	2.103	4.136	0.743
WCT	0.647	0.352	0.966	0.795	0.004***
NWC	2259	317	2330	117	0.042**
AST	0.631	0.835	0.681	0.674	0.244
EXP	1.238	1.332	0.946	0.706	0.001***
LogTA	15.56	1.415	15.49	1.498	0.747
LogCAP	14.87	1.477	13.72	1.585	0.520
AGE	14.87	7.161	20.25	5.537	0.046**
BLC	0.477	0.502	0.662	0.475	0.01***
IND	0.279	0.263	0.367	0.263	0.584
NDIR	2.258	0.489	3.558	1.523	0.02**
CONT	0.918	0.275	0.255	0.438	0.00***
MDD	0.209	0.409	0.302	0.461	0.006***
GENDER	0.942	0.235	0.523	0.502	0.00***
HAUSA	0.221	0.417	0.267	0.445	0.159
YARUBA	0.291	0.456	0.291	0.456	0.999
IGBO	0.255	0.438	0.244	0.432	0.727
FOREIGN	0.232	0.424	0.197	0.400	0.269
N	86	86	86	86	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as YARUBA (YARUBA), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN). Number of observation (N)

Table 4.21
Descriptive Statistics of Nigeria Sample

1 year prior to bankruptcy sample					
Variables	Bankrupt SMEs		Non-bankrupt SMEs		t-test
	Mean	St. D	Mean	St. D	
ROE	-0.844	2.175	0.199	2.422	0.02**
EBIT	-0.198	0.510	0.025	0.137	0.00***
TLA	1.709	1.894	0.982	1.504	0.092*
LTA	0.275	0.488	0.224	0.420	0.184
CLA	0.959	0.654	0.957	0.650	0.948
CLE	0.921	0.142	0.877	0.179	0.052*
LQT	1.339	4.698	1.906	2.675	0.428
WCT	0.932	0.761	0.928	0.762	0.986
NWC	2252	329.9	2326	103.5	0.027**
AST	0.371	0.268	0.645	0.486	0.002***
EXP	0.933	0.130	0.874	0.180	0.003***
LogTA	15.70	1.523	15.77	1.524	0.961
LogCAP	13.79	1.723	13.79	1.669	0.931
AGE	14.39	7.264	20.24	6.128	0.00***
BLC	0.362	0.484	0.655	0.479	0.015**
IND	0.017	0.131	0.017	0.131	0.999
NDIR	3.534	1.569	3.639	1.563	0.723
CONT	0.931	0.255	0.293	0.459	0.00***
MDD	0.206	0.408	0.293	0.459	0.034**
GENDER	0.551	0.501	0.557	0.501	0.999
HAUSA	0.206	0.408	0.310	0.466	0.012**
YARUBA	0.362	0.484	0.313	0.466	0.247
IGBO	0.259	0.441	0.242	0.431	0.671
FOREIGN	0.173	0.381	0.138	0.347	0.309
N	58	58	58	58	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (Hausa), ethnicity of managing director as Yoruba (Yoruba), ethnicity of managing director as Igbo (Igbo), ethnicity of managing director as Foreign (Foreign). Number of observation (N).

The result also shows that bankrupt SMEs have high operating expenses (EXP) compared to non-bankrupt SMEs. Firms with high expense ratio are expected to experience high probability of bankruptcy due to the inability of the management to control cost that will trim the company's profit (Anderson et al., 2007). Both

bankrupt and non-bankrupt SMEs rely on long term and short term liabilities to finance their day-to-day business operations (Altman et al. 2010). When comparing the means differences between the groups, bankrupt SMEs take up more debt finance than non-bankrupt SMEs. The total debt to total asset (TLA) for bankrupt SMEs is 89.8 percent while non-bankrupt SMEs have 44 percent for 3-year prior to bankruptcy sample. However, the TLA of bankrupt SMEs is 163.9 percent compared to 106.9 percent for 2-year prior to bankruptcy sample. For the 1-year prior sample, the TLA of bankrupt SMEs is 170.9 percent against 98.2 percent for non-bankrupt SMEs. The closer the companies move into bankruptcy, the higher the liabilities. This is in contrast to the non-bankrupt SMEs. This finding is similar to Abdullah et al. (2016), Behr and Guttler (2007) and Chotima (2013). Liquidity (LQT) also follows a similar pattern. Bankrupt SMEs have lower liquidity than non-bankrupt SMEs but both groups have relatively sufficient liquidity as the ratio is above 1 except for the 3-year prior to bankruptcy sample. The ratio for the bankrupt SMEs is 1.34 times versus 1.91 times for the non-bankrupt SMEs, 1.58 times versus 2.10 times and 0.57 times versus 2.38 times for the respective 1-year, 2-year and 3-year prior to bankruptcy samples.

The average age (AGE) of bankrupt SMEs is about 14 to 16 years while non-bankrupt SMEs have been in the operations for more than 20 years. The longer a company survives, the less likely it will fail, which is in line with previous studies (eg. Abdullah et al., 2016; Altman et al., 2010; Blanco et al., 2007; Shane, 1996). Business location (BLC) shows that majority of the bankrupt SMEs are located in less industrialised states compared to non-bankrupt SMEs that are mostly located in the industrialised states (Kano, Lagos, Rivers, Abuja and Delta) in Nigeria. This

suggests that SMEs in less industrialised states²⁶ are substantially riskier than their counterparts in industrialised states.

More so, the result indicates that as the SMEs approach bankruptcy (1-year and 2-year prior to bankruptcy samples), on average 93 percent of bankrupt SMEs are having controlling shareholder while only an average 27 percent of the non-bankrupt SMEs are having controlling shareholder. Probably the controlling shareholders of the bankrupt SMEs are given considerable power during either a reorganisation or liquidation of the company. Studies (Altman, 1998; Bhandari & Weiss, 1996) finds a strong deviation from absolute priority rule (APR)²⁷ in the US, that shareholders in reality receive payout without settling debt holders which represent 81 percent of the cases. There are violation in 78 percent cases of not settling unsecured creditors while secured creditors received full payout in only 92 percent cases with 8 percent violation (Altman, 1998; Bhandari & Weiss, 1996).

Furthermore, on the gender of managing director (GENDER), 80 percent of the bankrupt SMEs are having male managing director (MD) while only 62 percent among the non-bankrupt SMEs. For the non-bankrupt SMEs, the average board size

²⁶ Abia, Adamawa, Anambra, Akwa Ibom, Bauchi, Bayelsa, Benue, Borno, Cross River, Ebonyi, Enugu, Edo, Ekiti, Gombe, Imo, Jigawa, Kaduna, Katsina, Kebbi, Kogi, Kwara, Nasarawa, Niger, Ogun, Ondo, Osun, Oyo, Plateau, Sokoto, Taraba, Yobe, Zamfara. For more detail on Nigerian States, please refer to the following link, <https://www.nounportal.org/list-of-the-36-states-of-nigeria-and-their-capitals/>

²⁷ An absolute priority is a rule that stipulates the order of payment - creditors before shareholders - in the event of liquidation. The absolute priority rule is used in bankruptcies to decide what portion of payment will be received by which participants. Debts to creditors will be paid first and shareholders (partial owners) divide what remains.

is 4 directors while for the bankrupt SMEs the average board size is 3 directors. Both groups of SMEs have independent directors as their board members. The bankrupt SME's board on average consist of about 20 percent of independent members while non-bankrupt SMEs have an average of 35 percent of independent directors. Independent directors in some cases would benefit the small businesses such as better access to external resources and management competencies. Independent directors can also provide expert knowledge, monitoring services and reduces agency problem (Fama, 1980; Fama & Jensen, 1983). The National Code of Corporate Governance (2016) also advocates the presence of at least one independent director in the board of companies as they could help reduce agency problem between the managers and shareholders of the firm.

Moreover, 32 percent of bankrupt SMEs are managed by Yoroba, followed by Igbo 26 percent, Hausa 21 percent and foreign managing directors 19 percent. However, among the non-bankrupt SMEs, 29 percent are managed by Hausa, followed by Yoroba 26 percent, Igbo 25 percent and foreign managing directors 20 percent.

4.3.2 Diagnostic Tests for Logistic Regression

This section presents the diagnostic tests to check if the assumptions of the logistic regression model are met. The diagnostic tests include the multicollinearity test; the model fit test and model specification test.

4.3.2.1 Multicollinearity

Pearson correlation test is employed to test the relationship between the independent variables and the results are summarised in table 4.22. The finding shows that the

correlations among the variables are relatively low ranging from 0.004 to 0.43 and majority of the relationships are insignificant.

Several variables such as TLA against LTA, TLA against LQT, TLA against EBIT, TLA against LogTA, LTA against AST, CLA against NDIR, EXP against EBIT, WCT against NWC, AST against LogCAP, LogTA against LogCAP, LogTA against MDD, LogCAP against GENDER, LogCAP against CONT, AGE against GENDER, AGE against CONT, AGE against NDIR, IND against GENDER, IND against LNR and CONT against NDIR. Furthermore, EBIT against ROE, EBIT against NWC, EBIT against AST, EBIT against GENDER, EBIT against CONT, EBIT against MDD, BLC against Igbo, BLC against FOREIGN, GENDER against CONT, GENDER against NDIR, HAUSA against YARUBA, HAUSA against IGBO, YARUBA against IGBO, YARUBA against FOREIGN, GDP against CPI and GDP against EMPY are found to be significant at 1 percent level.

Moreover, TLA against NDIR, LTA against YARUBA, CLA against EXP, CLE against IND, CLE against FOREIGN, LQT against EXP, EBIT against LogTA, ROE against GENDER, ROE against NDIR, WCT against GENDER, AST against CONT, LogTA against NDIR, LogCAP against MDD, AGE against GDP, AGE against EMPY, GENDER against MDD, CONT against MDD, CONT against LNR, MDD against HAUSA, MDD against IGBO, HAUSA against FOREIGN, HAUSA against GDP, IGBO against FOREIGN, GDP against LNR and LNR against EMPY are also found to be significant at 5 percent level.

Table 4.22

Pearson Correlation Analysis of Nigerian Sample

Variables	TLA	LTA	CLA	CLE	LQT	EXP	EBIT	ROE	WCT	NWC	AST	LogTA	LogC AP	Age
TLA	1													
LTA	.21***	1												
CLA	.15	.01	1											
CLE	.01	-.02	.03	1										
LQT	-.22***	.15	.10	-.02	1									
EXP	-.09	-.11	.17**	.05	-.15**	1								
EBIT	-.27***	-.03	-.12	-.04	.09	-.34***	1							
ROE	-.13	.03	-.04	-.02	.11	-.03	.37***	1						
WCT	.09	-.09	-.01	-.05	-.11	-.03	.06	.08	1					
NWC	-.03	.05	-.05	-.03	.07	-.1	.26***	.07	.21***	1				
AST	-.12	-.23***	-.11	-.08	-.10	.1	.26***	.14	.14	.001	1			
LogTA	-.39***	.01	-.17**	.03	-.04	.09	.16*	.01	.02	-.02	.07	1		
LogCAP	-.02	.08	.14	-.03	.06	.09	-.13	-.16**	-.11	-.06	-.23***	.38***	1	
Age	.01	.07	-.09	-.02	-.03	-.08	.01	-.05	.04	.02	.09	.06	-.03	1
BLC	.03	-.04	.03	.02	-.06	.10	-.01	.15	.02	.01	.12	.09	-.06	.02
IND	.04	-.11	-.08	-.16**	.01	-.11	.11	-.01	.05	.06	.09	-.02	-.11	.08
GENDER	-.04	.01	.14	.12	.03	.15	-.22***	-.19**	-.18**	-.08	-.12	.15	.24***	-.23***
CONT	.07	.04	.09	.02	.02	.12	-.23***	-.11	-.14	-.05	-.16**	.11	.21***	-.33***
NDIR	-.19**	-.01	-.29***	-.12	.05	-.1	.16**	.15**	.07	.07	.07	.17**	-.02	.26***
MDD	-.12	-.10	.11	-.05	-.04	-.05	.20***	.06	-.03	.04	.08	-.21***	-.15**	.05
HAUSA	-.04	-.14	.03	-.08	-.01	.08	-.02	-.06	.06	.08	-.09	-.09	-.02	-.01
YAROBA	.03	.16**	.06	-.08	.03	.05	.01	.08	-.13	-.06	-.04	-.06	-.03	.03
IGBO	-.06	.05	-.09	.01	-.06	.03	.01	.01	.16**	.08	-.05	.01	.03	.04
FOREIGN	.08	-.08	.01	.17**	.03	-.09	-.04	-.03	-.08	-.1	.10	.15	.02	-.07
GDP	-.07	-.13	-.06	-.02	-.01	.01	.05	.03	-.06	-.02	.02	.05	-.02	-.15**
LNR	-.02	-.08	.09	.02	.02	.01	-.01	-.08	.02	-.06	-.03	-.10	.07	.09
CPI	-.04	.06	-.11	-.03	-.07	.01	.06	.08	.13	.02	-.03	.03	-.09	-.03
EMPY	-.08	-.09	-.02	.04	.05	-.05	.04	.05	-.04	.07	-.03	.06	.06	.16**

Table 4.22 (continued)

Variables	BLC	IND	GENDER	CONT	NDIR	MDD	HAUSA	YAROA	IGBO	FOREIGN	GDP	LNR	CPI	EMPY
BLC	1													
IND	-.08	1												
GENDER	-.07	-.20***	1											
CONT	-.06	-.06	.43***	1										
NDIR	.04	.07	-.22***	-.33***	1									
MDD	-.03	.10	-.16**	-.19**	-.12	1								
HAUSA	.11	-.01	.1	-.10	.10	.16**	1							
YAROA	-.01	.05	-.02	.10	-.08	.06	-.15***	1						
IGBO	-.29***	-.04	-.02	.02	-.02	-.15**	-.14***	-.16***	1					
FOREIGN	.19***	.02	-.07	-.02	-.08	-.08	-.13**	-.14***	-.13**	1				
GDP	-.1	-.06	.05	.08	-.05	-.06	-.16**	.01	.13	.02	1			
LNR	-.14	.21***	-.03	-.16**	.06	.12	-.02	-.06	.11	-.01	-.15**	1		
CPI	-.04	-.04	.02	.04	.02	.02	-.05	.12	-.05	-.03	-.28***	-.06	1	
EMPY	-.08	-.07	.004	.05	-.01	-.01	-.06	.04	.02	-.01	.3***	-.18**	-.12	1

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yaroba (YAROA), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY).

Table 4.23

Variance inflating factor

Variables	R²	VIF = 1/(1-R²_j)
EBIT	0.269	1.368
ROE	0.306	1.381
TLA	0.143	1.167
LTA	0.573	2.321
CLE	0.426	1.777
CLA	0.354	1.548
LQT	0.548	2.231
WCT	0.265	1.971
NWC	0.093	1.114
AST	0.227	1.292
EXP	0.490	1.974
LogTA	0.462	1.852
LogCAP	0.389	1.628
AGE	0.242	1.346
BLC	0.209	1.267
GENDER	0.141	1.154
MDD	0.246	1.328
CONT	0.336	1.531
NDIR	0.482	2.006
IND	0.319	1.467
HAUSA	0.421	1.727
YARоба	0.376	1.603
IGBO	0.511	2.045
FOREIGN	0.448	1.812
GDP	0.179	1.223
LNR	0.082	1.100
CPI	0.152	1.198
EMPY	0.052	1.065

Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yaroba (YARоба), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY).

Multicollinearity is not a threat to this study as indicated by the low pair-wise correlation among the variables. The variance inflating factor (VIF) test is reported in table 4.23 that check for multicollinearity problem. The result shows that the R²

are relatively low for all the variables, VIF ranges from 1.062 to 2.321 which is less than the critical value of 10.

4.3.2.3 Model Specification Test

Table 4.24 presents the result of the Linktest which is the general model specification for logistic regression models. To pass the Linktest, it is expected that $_hatsq$ should be insignificant (Pregibon, 1980). The table shows that model 1 (1-year and 3-year prior to bankruptcy samples), model 2 (1-year and 2-year prior to bankruptcy samples) and particularly model 3 (1-year, 2-year and 3-year prior to bankruptcy samples) were correctly specified. However, model 1's 2-year prior and model 2 3-year prior to bankruptcy sample $_hatsq$ is statistically significant at the 10 and 1 percent level respectively. Overall, the finding confirm that the study has selected meaningful predictors.

Table 4.24
Model Specification Test (Linktest) Nigeria Sample

	Model 1		Model 2		Model 3	
	Linktest	p-value	Linktest	p-value	Linktest	p-value
1-Year Prior	$_hat$	0.000***	$_hat$	0.000***	$_hat$	0.000***
	$_hatsq$	0.116	$_hatsq$	0.868	$_hatsq$	0.215
2-Year Prior	$_hat$	0.000***	$_hat$	0.000***	$_hat$	0.023**
	$_hatsq$	0.075*	$_hatsq$	0.965	$_hatsq$	0.972
3-Year Prior	$_hat$	0.000***	$_hat$	0.000***	$_hat$	0.000***
	$_hatsq$	0.633	$_hatsq$	0.001***	$_hatsq$	0.249

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combination of model 1 and 2.

4.3.2.2 Models Fit Test

The result of the Hosmer–Lemeshow test is presented in table 4.25. The test suggests that model 1, model 2 and model 3 are adequate and fit the data because the p-value are insignificant which indicates that the models are consistent with the data. This can be observed in the p-value of model 1 (0.981, 0.271 and 0.863 for the respective 3-year, 2-year and 1-year prior to bankruptcy samples), model 2 (0.208, 0.932 and 0.689 for the respective 3-year, 2-year and 1-year prior to bankruptcy samples) and model 3 (0.914, 0.996 and 0.996 for the respective 3-year, 2-year and 1-year prior to bankruptcy samples). This suggests that the predictors can be used to detect bankruptcy among small and medium size enterprises in Nigeria.

Table 4.25
Models Fit Test Nigeria Sample

	Hosmer-Lemeshow Test		
	3-year Prior sample	2-year Prior sample	1-year Prior sample
Model 1	1.687 (0.981)	9.919 (0.863)	3.932 (0.863)
Model 2	10.886 (0.208)	3.032 (0.932)	5.650 (0.689)
Model 3	3.302 (0.914)	1.271 (0.996)	1.273 (0.996)

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Numbers in parenthesis represent p-value.

4.3.3 Logistic Regression Models Analysis

This section present the results from the logistic regression²⁸ using the explanatory variables shown in table 4.26. The objective is to identify significant predictors of bankruptcy among SMEs in Nigeria.

²⁸ The results presented in table 4.8 shows only the significant variables from the models. The full results (significant and non-significant variables) are presented in Appendix 4

4.3.3.1 Model 1: Financial and Non-financial Variables

Tables 4.26 present the results of the logistic regression for model 1. The debt ratio (TLA), profitability (EBIT), the age of business (AGE) and business location (BLC) of the SMEs in all samples are found to be significant with the expected sign. The findings show that debt ratio (TLA) is significantly positive in predicting bankruptcy among SMEs at the 1 percent level for the 3-year prior to bankruptcy sample and at the 10 percent level for the 2-year and 1-year prior to bankruptcy samples. SME with huge debt liabilities is likely to go bankrupt due to the high level of financial risk. When the debt ratio is high, the principal and interest payments take a significant amount of the company's profit. This is a hiccup of financial performance that will subsequently results in bankruptcy if SMEs are not able to fulfil their obligations.

This is also in line with the trade-off theory where higher level of leverage result in the trade-off between interest tax shield enjoyed by the firm and an increase of financial risk (Hirshleifer, 1966; Robichek & Myers, 1965). Similar finding is also reported by Abdullah et al. (2016), Behr and Guttler (2007) and Chotima (2013) using SMEs sample. Furthermore, high debt implies a relatively larger claim on the firm's assets by creditors. From a creditor perspective, higher debt intensifies the conflicts of interest with shareholders and the concern over excess distribution (Shoorvarzy, Tuzandehjani & Garkaz, 2012). LTA and CLE are positive and significant but only in the 3-year prior to bankruptcy sample.

Table 4.26

Logistic regression of Nigerian Sample

Variables	Model 1			Model 2			Model 3		
	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	37.683***	-7.540	-2.418	1.265**	0.564	-0.914	80.640***	-22.057	44.586
EBIT	-14.815***	-10.048***	-8.968***				-28.483***	-17.791**	-18.996*
ROE	-9.344*						-22.075***		-1.901*
TLA	1.987***	0.3581*	0.424*				3.845***	1.015*	2.581*
CLE	3.076*						8.161**	1.116*	
LQT	-0.706**		-0.173**				-1.267***		0.790**
WCT		-1.432**						-3.311*	
EXP	2.214**		5.016**				3.094*		
AST			-1.094***						-2.281**
LogCAP		0.414*					0.699*	0.997**	
AGE	-0.117***	-0.218***	-0.294***				-0.139***	-0.315***	0.950**
BLC	-1.488***	-1.228**	-1.651**				-3.508***	-4.332**	-8.567**
MDD				-0.832***					
CONT				1.322***	3.986***	3.918***		6.194***	15.630**
NDIR				-0.519***	-1.748***		-0.631**	-1.212**	
IND				-2.009***			-5.518**		
GENDER					2.716***	-0.968*	-2.528*	3.431**	
EMPY					153.75**		298.89**		514.67*
CPI								4.531*	
IGBO							3.944**		
HAUSA							3.372**		
McFadden R ²	0.781	0.533	0.551	0.286	0.618	0.389	0.860	0.844	0.827
Observation (N)	276	138	94	276	138	94	276	138	94

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Igbo (IGBO), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY).

Profitability measured by EBIT is negative and significant at the 1 percent level for all the prior year to bankruptcy samples in predicting bankruptcy among SMEs. The result shows that profitable SME face lower bankruptcy risk. This could be that profitable SMEs are able to meet their short and long term commitments while unprofitable SMEs are unlikely to meet their financial obligations. This is because unprofitable SMEs are not able to reinvest as there is no sufficient profit and therefore depend on short-term or long-term debt financing for its assets and business activities. Abdullah et al. (2016), Arslan and Karan (2009), Fidrmuc et al. (2006), Fidrmuc and Hainz (2010), and Sirirattanaphonkun and Pattarathammas (2012) report that profitable SMEs are less likely to go bankrupt compared to less profitable SMEs. ROE as the second measure of profitability is also negative in predicting bankruptcy among SMEs but is only significant at the 10 percent level for the 3-year prior to bankruptcy sample.

Furthermore, the results show that liquidity ratio (LQT) is negatively significant in predicting bankruptcy among SMEs in Nigeria. LQT is significant at the 5 percent level for the 3-year and 1-year prior to bankruptcy samples. A negative coefficient suggests that the lower the liquidity the more likely an SME is going to bankrupt. Previous studies also find liquidity as one of the main determinants of bankruptcy for small businesses, given its significant effect on business sustainability (Abdullah et al., 2016; Arslan & Karan 2009; Chotima, 2013; Fidrmuc et al., 2006; Fidrmuc & Hainz 2010; Khorasgani, 2011; Lugovskaja, 2009; Monelos et al., 2011; Monelos et al., 2012; Moscalu, 2012). WCT is one of the measure of liquidity which is also negative but significant only in the 2-year prior to bankruptcy sample. Moreover, the result shows that expense ratio (EXP) is a positive predictor of SMEs

bankruptcy and significant at the 5 percent level for the 3-year and 1-year prior to bankruptcy samples. A high expense ratio indicates inefficiency of managers to control costs, whereas a low expense ratio indicates efficiency to control costs (Anderson et al., 2007). Firms with high expense ratios are expected to experience high probability of bankruptcy. It could also signal significant extent of managerial discretion in spending company resources among the Nigerian SMEs.

Age of SME (AGE) is negative and significant (at 5% level for 3-year, 2-year and 1-year prior to bankruptcy samples) in predicting bankruptcy among SMEs in Nigeria. The longer the SME is in business, the less likely it is to fail. Younger firms are more likely to fail because they face greater variability in their cost functions while they are learning about their industry and management capabilities (Jovanovic, 1982). Thus, the longer a company has existed, the higher the chance of it to remain in operation as a result of their ability to learn, experience and have more competitive advantages over the younger companies. When firms become older, they become more transparent and are likely to gain access to cheaper debt financing given the well-established reputation and good relationship with creditors (Coad, Segarra & Teruel, 2013) and thus, older firms are less likely to go bankrupt. The finding is in line with previous studies like Abdullah et al. (2016), Altman et al. (2010), Blanco et al. (2007) and Shane (1996).

Moreover, the finding shows that business location (BLC) is negative and a significant driver of SME's bankruptcy in Nigeria. BLC is significant at the 1 percent for 3-year prior and at the 5 percent level for 2-year and 1-year prior to bankruptcy samples. The finding shows that companies in less industrialised states

are likely to go bankrupt than their counterparts located in more industrialised states (Abuja, Delta, Lagos, Kano & Rivers). This is because SMEs in less industrialised states are exposed to high risk of uncertainty since they operate in a more difficult and uncertain economic environment. Less industrialised states are lack of good infrastructure, market potentials, and vibrant economic environment. The result is consistent with the study of Behr and Guttler (2007) which shows that regional factor is an important driver of SME's bankruptcy in Germany.

4.3.3.2 Model 2: Governance and Macroeconomic Variables

The results from model 2 shows that controlling shareholder (CONT) is significant and positive in predicting bankruptcy among SMEs in Nigeria. The predictor is significant at the 1 percent level for the 3-year, 2-year and 1-year prior to bankruptcy samples. This indicates that the higher the SMEs' level of controlling shareholders, the higher the likelihood of bankruptcy will be. When ownership concentration exceed certain limits, controlling shareholders tend to use corporate resources for their own interests by expropriating the interest of other shareholders and stakeholder (Shleifer & Vishny, 1997). The transfer of company resources by controlling shareholders come in many forms including consuming perks, setting excessive salaries, and making inefficient investment. This expropriation problem by controlling shareholders is likely to increase the likelihood of bankruptcy. In a similar vein, Abdullah et al. (2016) finds that controlling shareholder have a positive significant impact on predicting bankruptcy among SMEs in Malaysia.

Furthermore, board size (NDIR) is found to be significantly related to bankruptcy at the 1 percent level for the 3-year and 2 year prior to bankruptcy samples. The

negative coefficient suggests that board size reduces the probability of SMEs bankruptcy due to increase in monitoring. Moreover, the company can have access to diverse skills and expertise from the board members and access to more resources and information that would assist the management in formulating strategies (Lehn, Sukesh, & Zhao, 2004). This is consistent to Abdullah et al. (2016) and Keasey and Watson (1987) who also find board size to be significant and negatively related to SME bankruptcy in Malaysia and the UK respectively.

The results of the gender of managing director (GENDER) generate a mixed finding. For 2 year prior to bankruptcy, the gender of managing director is positive and significant in predicting bankruptcy among SMEs at 1 the percent level for 2-year prior to bankruptcy sample. The results show that male managing directors are more prone to bankruptcy among SMEs than the female. This is because female managing directors will make more conservative decisions than male, and therefore, they are more risk averse than male. The risk level of firm manage by female would be smaller than firms managed by male (Vandergrift & Brown, 2005; Wei, 2007). Female managing director are believed to be more concerned with ethical behaviour and would extract less personal benefits from the company compared to male managing director (Barber & Odean, 2001; Bliss & Potter, 2002; Ford & Richardson, 1994). The results is also in line with the finding of Abdullah et al. (2016) where they found that male managing directors are more likely to fail among the Malaysian SMEs.

However, in the 1 year prior to bankruptcy sample, the gender of managing director is found to be negative and significant predictor of SMEs bankruptcy at the 10

percent level. The results indicate that male MD are less likely to fail compared to female MD. These mixed finding could be as a result of the glass cliff phenomenon. The glass cliff is the phenomenon of women in leadership roles during periods of financial crisis, when the probability of bankruptcy is high (Ryan, Alexander & Postmes, 2007). When companies are performing well under men leadership, there will not be change in leadership due to the glass ceiling. But when the company is in trouble and nearly going into to bankruptcy, then female leadership would be preferred. For example, companies may bring in women to take the leadership role because women are assumed to be sensitive, cooperative and are also thought to be more warm and relational, which may be more valuable in tough times (Ryan et al., 2011). Moreover, people believe women leaders are better-suited to lead stressed unhappy companies because they are felt to be more nurturing, creative, and intuitive and seen as good people managers (Haslam & Ryan, 2008). However, the finding of the study shows that the female MD could not succeed in turning around the financial distress company, hence the negative coefficient in the 1-year prior to bankruptcy sample.

Proportion of independent directors (IND) on board is negatively significant to bankruptcy prediction. The variable is significant only in 3-year prior to bankruptcy sample at the 1 percent level. The presence of independent directors in SMEs board is likely to reduce bankruptcy because they contribute effective monitoring and serve as a disciplining tool for managers. This will increase the independence and effectiveness of an SME's board of directors (Daily & Dalton, 1994; Elloumi & Gueyié, 2001). The finding is consistent with Ciampi (2015) who finds that independent directors significantly reduce the probability of bankruptcy among

SMEs in Italy. Furthermore, the finding is in line with the agency theory. Independent directors can reduce agency problem between the managers and shareholders of the firm and improve effectiveness of strategic decisions (Brickley & James, 1987; Byrd & Hickman, 1992). More so, the National Code of Corporate Governance (2016) also recommends at least the presence of one independent director on the board of companies.

Similarly, duality of managing director (MDD) is also found to be a negative and significant predictor of bankruptcy among SMEs in Nigeria. MDD is significant at 1 percent level for 3-year prior to bankruptcy sample. A managing director cum chairman of the board is likely to reduce bankruptcy. This finding supports the stewardship theory. Accordingly, CEOs are not an opportunistic shirker, but essentially wants to do a good job and to be a good steward of the corporate assets. Managers are perceived to be motivated by a need to achieve higher performance in order to gain key satisfaction and to exercise responsibility and authority (Kim, Al-Shammari, Kim, & Lee, 2009). The results are consistent with the finding of Ciampi (2015) using Italian SMEs.

Unemployment rate is the only macroeconomic variables that is significant at the 5 percent level for the 2-year prior to bankruptcy sample and is positively related to bankruptcy prediction of SMEs in Nigeria. SMEs are significant contributors to employment in Nigeria. In general, high unemployment rate indicates an underperforming economy or the economy is in recession. During this business cycle, businesses experience fall in consumer demand and many investment projects already undertaken begin to look unprofitable. Orders will be cut, inventory levels

will be reduced and business failures will occur as firms find themselves unable to sell their goods. The finding is consistent with Everett and Watson (1998), Hudson, (1989) and Millington (1994). They report a significant positive relationship between unemployment rates and bankruptcy.

4.3.3.3 Model 3: Model 1 and Model 2 Combined

Model 3 consists of all the categories of variables used in the study namely financial, non-financial, corporate governance and macroeconomic variables. The model also uses 3-year, 2-year and 1-year prior to bankruptcy samples. The results show that EBIT, ROE, TLA, LTA, CLE, LQT, WCT, AST, AGE and BLC are the only financial and non-financial variables that are significant in model 3. Similarly, the results show that CONT, NDIR, IND, GENDER and EMPY are the corporate governance and macroeconomic variables that are statistically significant in model 3.

The finding shows a negative and significant relation between profitability (EBIT and ROE) and SMEs bankruptcy. EBIT is statistically significant at the 1 percent level for the 3-year prior to bankruptcy sample, at the 5 percent level for the 2-year prior to bankruptcy sample and at the 10 percent level for the 1-year prior to bankruptcy sample. ROE is significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 10 percent level for the 1-year prior to bankruptcy sample. The finding shows that higher level of profitability would reduce the probability of SME going bankrupt. Profitable SMEs are more likely to use more of their retained earnings (at zero cost issuance) as a major source of finance as proposed by the pecking order hypothesis (Myers, 1984) to further growth their

business operation and finance working capital requirement. Hypothesis 1 is supported. High level of debt liabilities will result in higher probability of bankruptcy among SMEs. Debt ratios (TLA & CLE) is found to have a positive correlation with SMEs bankruptcy, thus supporting hypothesis 2 that SMEs with high debt liabilities are more likely to go bankrupt. Total debt to total asset (TLA) is significant at the 1 percent level for the 1-year prior to bankruptcy sample and at the 10 percent level for the 2-year and 1-year prior to bankruptcy samples. Current liabilities to total equity (CLE) is significant at the 5 percent level for the 3-year prior to bankruptcy sample and at the 10 percent level for the 2-year prior to bankruptcy sample. The result shows that high amount of debt would lead SMEs to bankruptcy. This also consistent with the trade-off theory where bankruptcy risk will outweigh the interest tax benefit enjoyed by the company due to high gearing (Hirshleifer, 1966; Robichek & Myers, 1965).

Furthermore, liquidity ratios (LQT & WCT) are found to have a negative coefficient and significant relationship with SMEs bankruptcy. The more liquid an SME is the less likely it is to go bankrupt. LQT is significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 5 percent for the 1-year prior to bankruptcy sample. WCT is significant at the 10 percent level for the 2-year prior to bankruptcy sample. Therefore, hypothesis 3 is supported.

Hypothesis 4a and 4b are supported. High asset turnover ratio (AST) is likely to reduce SMEs bankruptcy. The result shows that AST has negative and significant relationship with SME bankruptcy. A higher ratio is indicative of greater efficiency in managing asset, and how fast a company is able to generate sales through the use

of its assets. Furthermore, the results show expense ratio (EXP) is a positive predictor of SMEs bankruptcy and significant at the 10 percent level for the 3-year to bankruptcy samples. Firms with high expense ratios are expected to experience high probability of bankruptcy. It could also signal significant extent of managerial discretion in spending company resources among Nigerian SMEs.

Size (LogCAP) is found to have a positive and significant relationship with SMEs bankruptcy. The variable is significant at the 10 percent level for the 3-year prior to bankruptcy samples and at the 5 percent level for the 2-year prior to bankruptcy samples. The larger the size of a company, the higher is the probability of bankruptcy. This could be that large firms as a result of complexity in their internal and excessive administrative processes. This will lead to slow of information flow and decision making. As such smaller firms are more flexible and faster in responding and making decisions. This will enable them to cope with external changes. Hall and Young (1991) and Thornhill and Amit (2003) reports that large firms are more likely to fail due to external causes (such as environment, competition and demand). Additionally, large firm overtime becomes too confident in decision making due to past experience believing things will worked out in the future. However, this would lead to less scrutiny in decision making and evaluation. There should be a constant adjustments in strategies overtime to anticipate continuously changing business environment, customer needs and counter-tactics by competitors. Hypothesis 5 is supported.

The finding shows that business location (BLC) has a negative and significant correlation with SMEs bankruptcy. SMEs in less industrialised states are more

likely to go bankrupt compared with SMEs in more industrialised states. BLC is significant at the 1 percent level for the 3-year prior to bankruptcy sample and at the 5 percent level for the 2-year and 1-year prior to bankruptcy samples. Hypothesis 6 is supported. A negative and significant relationship is found between age of SME (AGE) and bankruptcy. The results show that younger SMEs are more likely to go bankrupt compared with older SMEs. The variable is negative and significant at the 1 percent level for the 3-year and 2-year prior to bankruptcy samples and at the 5 percent level for the 1-year prior to bankruptcy sample. Younger SMEs are likely to fail compared to older SMEs due to lack of experience in the business environment and growth development potentials. Hypothesis 7 is supported.

Larger number of directors on an SME board reduces the likelihood of bankruptcy. NDIR is found to have a negative coefficient and significant at the 5 percent level for the 3-year and 2-year prior to bankruptcy samples. Large boards are associated with better performance. Hypothesis 9 is supported. Consistent with hypothesis 10, controlling shareholder (CONT) is found to be significantly and positively correlated with SMEs bankruptcy. These shows that presence of a controlling shareholder is associated with SMEs bankruptcy. CONT is significant predictor of bankruptcy at the 1 percent level for the 2-year prior to bankruptcy sample and at the 5 percent level for the 1-year prior to bankruptcy sample. Hypothesis 11 is supported. The presence of independent directors (IND) on SMEs boardroom is found to have a negative and significant correlation with bankruptcy. The variable is significant only in the 3-year prior to bankruptcy sample at the 1 percent level.

Gender of managing director (GENDER) is negative and significant at 10 percent level for the 3-year prior to bankruptcy sample. The results show that female managing director of an SME is more likely to go bankrupt compared to male counterpart. However, for the 2-year prior sample, GENDER is positive and significant at the 5 percent level. This reveals that male managing director of an SME is more likely to go bankrupt compared to female counterpart. As mentioned earlier, these mixed finding could be due to the glass cliff phenomena. The finding shows that HAUSA and IGBO managing directors have a positive coefficient and statistically significant at the 5 percent level for the 3-year prior to bankruptcy sample. This indicates that SMEs managed by HAUSA and IGBO managing directors are more likely to go bankrupt compared to SMEs managed by non-HAUSA and IGBO managing directors. The HAUSA comes from the northern part of Nigeria, whom are very tradition and conservative in the way they run business. HAUSA managing director tend to resist change, discourage creativity and innovation and tend to stick to the old ways of doing things. Therefore, referring to the Hofstede model, it is reasonable to believe SMEs run by HAUSA managing director will be less innovative, uncertainty avoidance, high masculinity and high power distance.

Hypothesis 15 is also supported. Growth in unemployment rate (EMPY) is positive and significant at the 5 percent level for the 3-year prior to bankruptcy sample and at the 10 percent level for the 1-year prior to bankruptcy sample in predicting bankruptcy among SMEs. The higher the unemployment rate the more likely an SME to go bankrupt. With the high unemployment rate, fewer people have jobs, businesses would experience low consumer demands for goods and services. As a

result, businesses will experience lower sales revenue and are likely to see a fall in profits. Additionally, inflation rate is found to have a positive and significant relationship with SMEs bankruptcy. The inflation rate is significant at the 10 percent level for the 2-years prior to bankruptcy sample. The higher the inflation rate the more likely an SME is to go bankrupt. Changes in the level of inflation can affect the volatility of firm's cash flows. Businesses may find it difficult to compete in the market especially from foreign competition due to higher prices and higher cost of production and debt-servicing and hence reducing the company's profits and cash flows (Bhattacharjee, Higson, Holly & Kattuman, 2002). Therefore, hypothesis 16 is supported.

4.3.4 Models Performance and Validation of Logistic Regression

Table 4.27 provides a summary of the models classification rate for the estimated (training) and holdout (validation) samples. In a perfect model, all cases will be on the diagonal and the overall percent correct will be 100 percent. In this study, model 1 has an overall accuracy rate of 93.6, 85.6 and 84 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. The holdout sample for model 1 has an accuracy rate of 88.4, 81.8 and 81.8 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples. This is a considerable improvement on the classification rate with the constant model²⁹. Therefore, the model with predictors is a significantly better model.

²⁹ The constant model presents the results where only the constant included before any coefficients (independent variables) are entered into the equation. Logistic regression compares this model with a model including all the predictors (independent variables) to determine whether the latter model is more appropriate.

Table 4.27

Logistic regression classification rate for both estimated and holdout sample for Nigeria

	Estimated Sample (Training)			Holdout Sample (Validation)		
	3-year	2-year	1-year	3-year	2-year	1-year
Model 1	93.6%	85.6%	84%	88.4%	81.8%	81.8%
Model 2	78.9%	87.1%	87.2%	73.9%	87.9%	77.3%
Model 3	97.1%	95.7%	93.1%	85.5%	87.9%	81.8%
Observation	276	138	94	68	34	22

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Observation represents number of SMEs in the analysis.

Furthermore, model 2 accuracy rates are 78.9, 87.1 and 87.2 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples for the estimated sample. The accuracy rate of model 2 is the lowest compared to model 1 and model 3 for the 3-year prior to bankruptcy sample. Moreover, the result of the holdout sample for model 2 accuracy rate is 73.9, 87.9 and 77.3 percent for 3-year, 2-year and 1-year prior to bankruptcy. The accuracy rate of model 2 holdout sample is also the lowest compared to the holdout sample accuracy of model 1 and model 3 for 3-year and 1-year prior to bankruptcy samples. This could be that a bankruptcy prediction model that includes only governance and macroeconomic variables is not a sufficient and suitable predictive model. However, model 3 that combined both financial, non-financial, corporate governance and macroeconomic variables provide the highest predictive accuracy rate for both estimated and holdout sample. The accuracy rate of the estimated sample is 97.1, 95.7 and 93.1 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples, respectively. The accuracy rate of the holdout sample is 85.5, 87.9 and 81.8 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples, similar to that of Altman and Sabato (2007), Behr and Guttler (2007) and Luppi et al. (2007).

Additionally, the results reveal that as we move closer to bankruptcy (2-year and 1-year prior to bankruptcy samples), the accuracy rate of the estimated and holdout samples decreases. For example, the accuracy rate of the estimated sample for model 1 decreases by 8.5 percent from 3-year (93.6%) to 2-year (85.6%) prior to bankruptcy sample and decreases further by 2 percent from 2-year to 1-year (84%) prior to bankruptcy sample. A similar pattern is also observe in model 3 accuracy rate, decreasing from 97.1 percent in 3-year prior to bankruptcy sample to 95.7 percent in 2-year prior to bankruptcy sample and further decreasing to 93.1 percent for the 1-year prior to bankruptcy sample. For the holdout sample, model 1 accuracy rate decreased by 7.5 percent from 3-year (88.4%) to 2-year (81.8%) prior to bankruptcy samples. The results show that the models are less successful in predicting of bankruptcy as we move closer to the bankruptcy event.

4.3.4.1 Robustness tests on the Classification Accuracy of the Logistic Regression Models

Several tests are performed to observe whether the main results of the models are robust to various other model specifications. Receiver operating characteristic (ROC) curve analysis is another method to evaluate the predictive accuracy of the logistic regression model. The power of the model's predicted values to discriminate between positive and negative cases is quantified by the Area under the ROC curve (AUC). The AUC is a value that varies from 0.5 (discriminating power not better than chance) to 1.0 (perfect discriminating power). To perform a full ROC curve analysis on the predicted probabilities, the predicted probabilities are saved and use the predicted probabilities in ROC curve analysis. In this study, the ROC curve is based on the estimated sample.

Table 4.28

ROC classification rate for Nigeria Models

Models	3-year Prior Sample	2-year Prior Sample	1-year Prior Sample
Area Under the Curve			
Model 1	98.7%	93.4%	93.6%
Model 2	84.8%	95.6%	87.9%
Model 3	99.3%	99.4%	99.0%
Observation	276	138	94

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2.

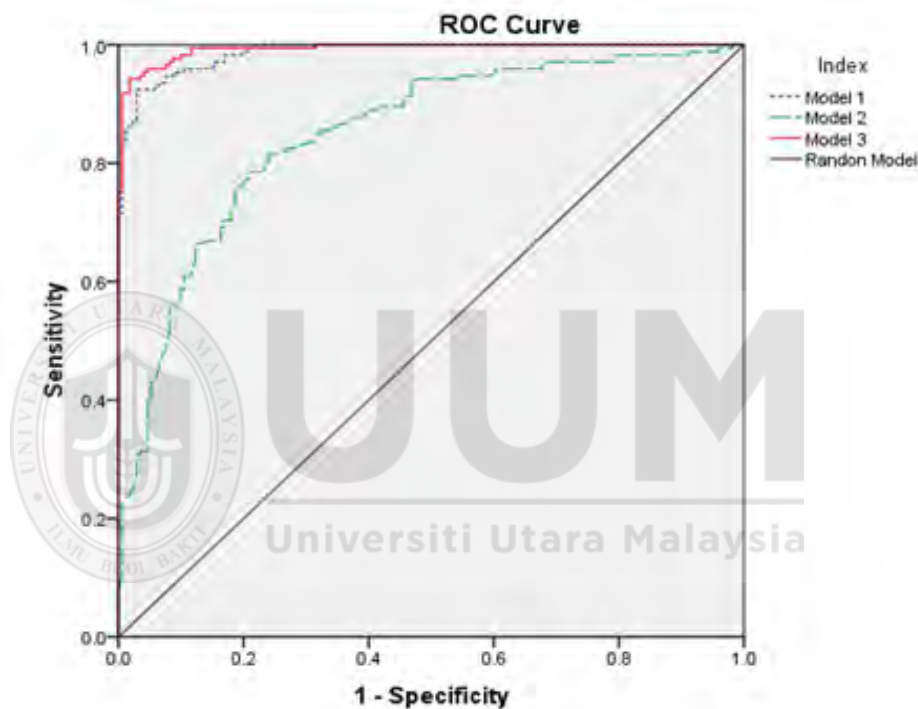


Figure 4.4

Comparison of ROC curves between models developed using 3-year prior to bankruptcy sample

To compute the ROC measure, the study compares the performance of model 1, model 2 and model 3 using the 3 year prior to bankruptcy samples which is presented in table 4.27. The result shows a similar outcome found with the estimated and holdout samples where the accuracy rate reduces as we move closer to the bankruptcy event. Model 1 and model 3 with a respective AUC of 0.987 and 0.993

are better than model 2 (with 0.848) in predicting bankruptcy. The result further illustrates that model 3 that incorporate, financial, non-financial, governance and macroeconomic variables has the largest area under the ROC curve than model 1 and model 2, suggesting that model 3 is the best model to predict bankruptcy among Nigerian SMEs. According to Hosmer et al. (2013), if the area under the ROC curve is between 0.8 and 0.9, the model is excellent at discriminating between the bankruptcy and non-bankruptcy companies. As such both models are excellent but model 3 is superior. This is clearly observed in figure 4.4.

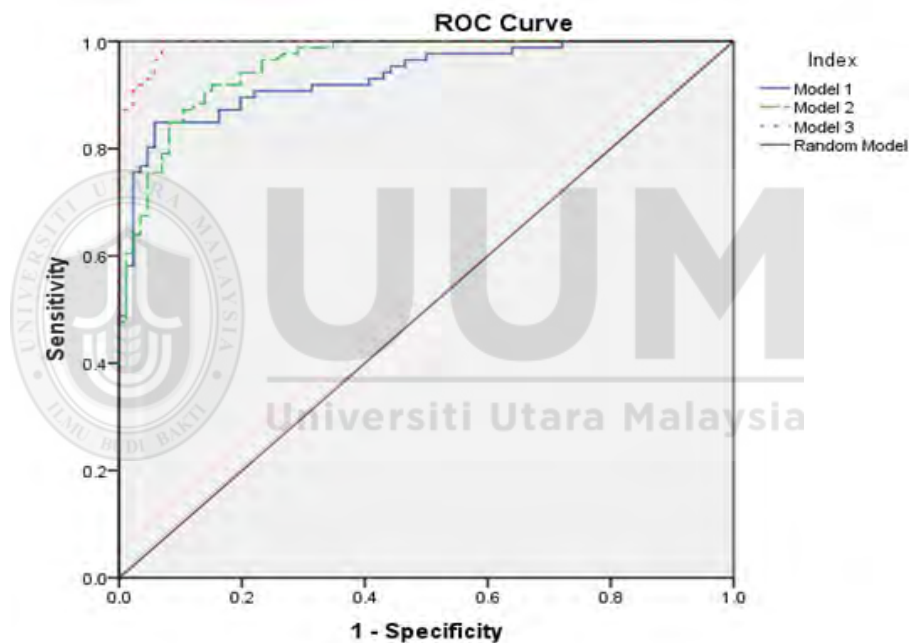


Figure 4.5
Comparison of ROC curves between models developed using 2-year prior bankruptcy sample

In a similar vein, figure 4.5 and 4.6 show that model 3 has achieved a higher predictive accuracy rate compared to model 1 and model 2. The AUC of model 3 for the 2-year prior to bankruptcy sample is 0.994, while 0.934 and 0.956 for model 1 and model 2 respectively. The result further illustrates that model 3 (AUC of 0.99)

that incorporates, financial, non-financial, governance and macroeconomic variables has the largest area under the ROC curve than model 1 (AUC of 0.936) and model 2 (AUC of 0.879) using 1-year prior to bankruptcy sample. In general, the finding shows that model 3 performs better than model 1 and model 2 in all the samples. The ROC curve analysis reinforces the classification accuracy rate of the estimated models reported in the previous section.

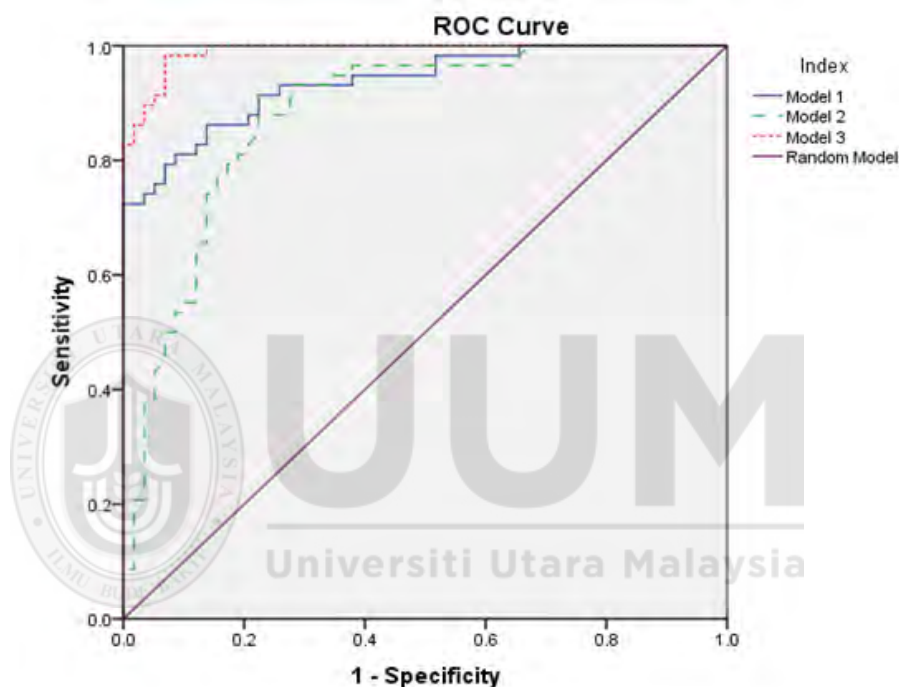


Figure 4.6
Comparison of ROC curves between models developed using 1-year prior sample

Further robustness test to check on the classification accuracy rate is implemented by looking at the Brier score an aggregate measure of disagreement between the observed outcome and a prediction that is, the average squared error difference. The Brier score decomposition is a partition of the Brier score into components that suggests reasons for discrepancy. These reasons fall roughly into three groups: 1)³⁰

³⁰ Problem 1 refers to simply overstating or understating the probabilities.

lack of overall calibration between the averages predicted probability and the actual probability of the event in the data, 2)³¹ misfit of the data in groups defined within the sample, and 3)³² inability to match actual 0 and 1 responses. The Brier score for a model can range from 0 for a perfect model to 0.25 for a non-informative model with a 50 percent incidence of the outcome.

Table 4.29
Brier Score for Nigeria Models

Models	3-year Prior Sample	2-year Prior Sample	1-year Prior Sample
Model 1	0.0467	0.0995	0.1000
Model 2	0.1577	0.0850	0.1332
Model 3	0.0312	0.0304	0.0411
Observation	276	138	94

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2.

Referring to table 4.29, similar to the ROC curve result, model 3 that incorporates financial, non-financial, corporate governance and macroeconomic predictors performed better in all samples. The Brier score for the 3-year prior to bankruptcy sample is 0.0312, 2-year prior to bankruptcy sample is 0.0304 and 1-year prior to bankruptcy sample is 0.0411. The results also reveal that as the bankruptcy date comes closer, the score of the models increases. As brier score is a way to verify the accuracy of a probability forecast. Smaller scores (closer to zero) indicate better forecasts.

³¹ Problem 2 refers to what is standardly called a goodness-of-fit test: the data are grouped, and the predictions for the group are compared with the outcomes.

³² Problem 3 refers to an individual-level measure of fit.

4.3.5 Endogeneity Test

As previously highlighted in section 4.2.5 for Malaysian analysis, evidence from prior studies suggests that there are two possible outcomes between corporate governance variables and bankruptcy. The study hypothesises that corporate governance indicators such as number of directors in board (NDIR), proportion of independent directors in board (IND) and managing director-duality (MDD) affects bankruptcy. However, it might be possible that these corporate governance indicators and bankruptcy are endogenously determined. In addition, prior literature also suggests that the relationship between corporate governance measures and bankruptcy is spurious due to endogeneity bias (Miglani et al., 2015; Schultz et al., 2015). Therefore, to investigate these concerns, the present study examined whether these variables suffer from endogeneity by performing the Durbin-Wu-Hausman test using the 2SLS regression. The Durbin-Wu-Hausman tests the null hypothesis that the residual values of NDIR, MDD and IND are jointly equal to zero. If the F-statistic is significant, then the null hypothesis would be rejected, suggesting that the variables are not exogenous and that endogeneity is present.

Using the instrumental variable approach i.e., 2SLS to address the endogeneity bias, table 4.30 presents the results. From the first-stage regression results, the instrumental variables used to run the endogeneity test are suitable based on the significance of the F-statistics and Hansen-Sargen test statistic for over-identification. The Hansen-Sargen test is statistical insignificant for NDIR (Sargan (score) $\chi^2(1) = 0.1708$, p-value = 0.6794) for the 3-year prior to bankruptcy sample and NDIR (Sargan (score) $\chi^2(1) = 0.0194$, p-value = 0.8891) for the 2-year prior to bankruptcy sample. The Hansen-Sargen test is also statistical

insignificant for IND (Sargan (score) $\chi^2(1) = 0.0526$, p-value = 0.8186) for the 3-year prior to bankruptcy sample, 2-year (Sargan (score) $\chi^2(1) = 0.0006$, p-value = 0.9936) and 1-year (Sargan (score) $\chi^2(1) = 0.0672$, p-value = 0.7955) prior to bankruptcy sample, indicating that the instrumental variable sets are valid (Stock & Yogo, 2005).

Table 4.30 present the results of the endogeneity test for model 2. The Durbin-Wu-Hausman test results show that the F-statistics of number of directors (NDIR) for 3-year prior (F-statistics = 21.567, p-value = 0.000) and 2-year prior (F-statistics = 7.886, p-value = 0.006) to bankruptcy are statistically significant at 1 percent level, thus confirming the presence of endogeneity problem. Similarly, the F-statistics of the Durbin-Wu-Hausman test results on the independent director (IND) is statistically significant in all the samples. The F-statistics for the 3-year prior to bankruptcy sample is 6.325 (p-value = 0.0124), 2-year prior to bankruptcy sample is 8.294 (p-value = 0.0045) and 1-year prior to bankruptcy sample is 7.172 (p-value = 0.0086). This confirm the presence of endogeneity as such 2SLS regression should be performed.

Table 4.30

The results of endogeneity test for Model 2 Nigerian Sample using Instrumental Variable Approach

Variables	3-Year Prior to Bankruptcy Sample			2-Year Prior to Bankruptcy Sample			1-Year Prior to Bankruptcy Sample	
	First Stage NDIR	First Stage IND	Second Stage Logistic Reg	First Stage NDIR	First Stage IND	Second Stage Logistic Reg	First Stage IND	Second Stage Logistic Reg
Constant	3.2057***	0.0184	3.5094***	3.1402***	0.3656***	54.022***	0.1254	8.5845**
GDP	-0.0662	-0.0434*		0.0210	-0.0108		0.0422	3.1742**
LNR	0.3867	0.2246		0.6519	0.7048**	63.489***	-0.1123	-12.526**
CPI	-0.1756	-0.0224		0.1548	-0.0271		-0.0330	2.6277**
EMPY	4.6824	-2.1617	30.2998**	8.7093	-2.1946		-1.0157	
GENDER	-0.2274	-0.0027		-0.3698	-0.1270**	-9.9550***	0.0526	
CONT	-1.1943***	0.0537*	1.0971***	-0.8040***	0.0551	1.3325**	-0.0984***	2.4756*
NDIR		0.0598***	-0.5842***		0.0118	-8.2269**	0.0697	
IND	4.0195***		-8.3338***	0.2393		-75.032***		-63.494**
MDD	-0.0951	-0.0045	-0.9449***	-0.7240***	0.0356		0.0433	2.3368*
HAUSA	0.2276	-0.0510	-0.1518**	0.5715**	0.0094	4.0099**	-0.0591	-5.0384***
IGBO	-0.1817	-0.0614*	-0.5238**	0.1682	-0.0189		-0.0249	-2.8685**
YORUBA	-0.2119	-0.0484		0.3479	0.0228	3.1793**	0.0193	
IND_IND		0.5611**			0.0202***		-0.0237**	
IND_NDIR	0.5910***			0.2671**				
R-squared	0.3500	0.2898		0.1865	0.0977		0.1386	
F-value	14.85	11.226		3.04	1.43		1.38	
	(0.000)***	(0.000)***		(0.000)***	(0.1554)		(0.0867)*	
Durbin-Wu-Hausman	21.5668	6.3246		7.8857	8.2944		7.1721	
	(0.0000)***	(0.0124)**		(0.0056)***	(0.0045)***		(0.0086)***	
Hansen-Sargan test	0.1708	0.0526		0.0194	0.00064		0.0672	
	(0.6794)	(0.8186)		(0.8891)	(0.9936)		(0.7955)	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yoruba (YORUBA), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY), industry-average number of directors (IND_NDIR), industry-average proportion of independent directors (IND_IND).

Table 4.31

The results of endogeneity test for Model 3 Nigerian Sample using Instrumental Variable Approach

Variables	2-Year Prior to Bankruptcy Sample		1-Year Prior to Bankruptcy Sample	
	First Stage	Second Stage	First Stage	Second Stage
	NDIR	Logistic Reg	NDIR	Logistic Reg
Constant	2.3772	-16.0851	-3.1133	35.6282
NDIR		-3.3765*		-1.2138**
MDD	-0.6171***		-0.3037	
EBIT	-0.0071	-18.287**	-0.7786*	-16.431**
ROE	0.0715		0.0410	-1.7868**
TLA	-0.0953	1.2509**	-0.0435	2.5476*
LTA	0.2042		1.0018*	
CTA	-1.6591***		-1.1323	
CLE	-0.1631		0.0787	
LQT	0.0066		0.0455	-0.6739**
WCT	0.0228	-4.0265**	-0.2089	
NWC	0.0008		0.0006	-0.0269*
AST	-0.0131		-0.1375	-2.4678**
EXP	-0.0412		0.4126	18.2898*
LogTA	0.0854		0.2475	2.3029*
LogCAP	0.0309	1.1183**	0.0982	
AGE	0.0268*	-0.2473**	0.0108	-0.8359**
BLC	-0.0127	-3.6092**	0.2311	-8.1089**
GENDER	-0.2388		-0.6357*	
IND	0.0473	-4.5222**	0.1359	
CONT	-0.6271***	5.8834***	-0.0943	14.474**
CPI	0.0075	3.4162**	-0.1550	
GDP	0.0182		0.1631	
LNR	1.2877		-1.8145	-32.754**
EMPY	-6.5664		46.869	439.704*
HAUSA	0.5105*		0.0611	
YARоба	-0.0040		0.0303	
IGBO	0.2713		0.3143	
IND_NDIR	0.1887**		0.3101***	
R-squared	0.3153		0.2445	
F-value	2.46		1.06 (0.4094)	
	(0.005)***			
Durbin-Wu-	6.7409		5.6125	
Hausman	(0.009)***		(0.0178)**	
Hansen-Sargan test	2.606 (0.9987)		0.7016 (0.4022)	

*, **, *** significant at 10 percent, 5 percent and 1 percent levels respectively. Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yaroba (YARоба), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN), yearly percentage changes in gross domestic product (GDP), yearly percentage changes in lending rate (LNR), yearly percentage changes in consumer price index (CPI) and yearly percentage changes in unemployment rate (EMPY),), industry-average number of directors (IND_NDIR).

However, the F-statistic of the Durbin-Wu-Hausman test is insignificant for managing director duality (MDD) for all the samples in model 2 as presented in table 4.32. The F-statistics for the 3-year prior to bankruptcy sample is 0.0593 (p-value = 0.808), 2-year prior to bankruptcy sample is 1.568 (p-value = 0.344) and 1-year prior to bankruptcy sample is 2.307 (p-value = 0.132). The results suggest that there is no evidence of endogeneity problem. Similarly, number of director's (NDIR) F-statistic of the Durbin-Wu-Hausman test is insignificant for 1-year prior to bankruptcy sample, where the F-statistic is 0.399 (p-value = 0.529), suggesting no indication of endogeneity. The variable MDD (for all the samples) and NDIR for 1-year prior to bankruptcy sample may not require the 2SLS regression. As suggested by Baum et al. (2003), in the absence of endogeneity, the results of 2SLS regressions are unacceptable and biased. In summary, the results estimated using the logistic regression in the main analysis are efficient due to the absence of endogeneity.

Additionally, table 4.31 presents the results of the endogeneity test for model 3 using the 2SLS. The finding shows that only NDIR for the 2-year and 1-year prior samples are affected by endogeneity problem (refer to table 4.32). The results from the Durbin-Wu-Hausman test show that the F-statistic of NDIR (F-statistic = 6.7409, p-value = 0.009) for the 2-year prior to bankruptcy sample and 1-year prior to bankruptcy sample (F-statistic = 5.6125, p-value = 0.0178) are significant, which confirm the presence of endogeneity.

Table 4.32

Durbin-Wu-Hausman test and Hansen-Sargen test for model 2 and 3 Nigerian sample

	Model 2								
	3-Year Prior Sample			2-Year Prior Sample			1-Year Prior Sample		
	NDIR	MDD	IND	NDIR	MDD	IND	MDD	NDIR	
Durbin-Wu-Hausman	21.57 (p=0.00)	0.06 (p=0.81)	6.32 (p=0.01)	7.89 (p=0.01)	1.57 (p=0.34)	8.29 (p=0.00)	2.31 (p=0.13)	0.39 (p=0.53)	
Hansen-Sargen test	0.17 (p=0.67)	0.69 (p=0.41)	0.05 (p=0.82)	0.02 (p=0.89)	0.22 (p=0.64)	0.01 (p=0.99)	2.91 (p=0.09)	5.65 (p=0.02)	
	Model 3								
	3-Year Prior Sample			2-Year Prior Sample			1-Year Prior Sample		
	NDIR	MDD	IND	IND	MDD	NDIR	IND	MDD	
Durbin-Wu-Hausman	0.15 (p=0.69)	0.04 (p=0.85)	3.26 (p=0.11)	0.80 (p=0.39)	1.85 (p=0.18)	6.74 (p=0.01)	0.06 (p=0.81)	0.93 (p=0.34)	
Hansen-Sargen test	4.59 (p=0.03)	1.54 (p=0.21)	0.05 (p=0.83)	0.78 (p=0.38)	0.42 (p=0.51)	2.61 (p=0.99)	1.44 (p=0.23)	2.07 (p=0.15)	

Note: Numbers in parentheses represents the respective p-values

The results of the endogenous variables (NDIR and IND) in table 4.30 and tables 4.31 for the 2SLS regressions remain unaffected and relatively consistent with the earlier finding in the logistic regression. The null hypotheses is that the regressors are exogenous is rejected. Therefore, NDIR and IND are endogenous regressors and the coefficients on the second stage of the 2SLS are more robust, appropriate and unbiased estimate to use. The findings from table 4.30 and table 4.31 show that the number of directors (NDIR) is negative and significant at the 1 percent level for the 3-year and 2-year prior to bankruptcy samples for model 2. NDIR is also negative and significant at the 1 percent level for the 2-year and 1-year prior to bankruptcy samples for model 3. The finding indicates that an increase in board size reduces the probability of bankruptcy among SMEs. Thus, it can be stated that larger board can decrease the probability of SMEs bankruptcy. This could be due to the diverse skills and experience from the individual board members the company could benefit from.

Furthermore, the result shows that the presence of independent director (IND) is also negative and significant at the 1 percent level for the 3-year, 2-year and 1-year prior to bankruptcy samples for model 2. The finding shows that IND reduces the probability of bankruptcy among SMEs. The presence of independent director could likely help SMEs to effectively monitor and serve as a disciplining device for managers thereby increasing the effectiveness of an SME board. Notably, the study finds that there is presence of endogeneity problem among some of the corporate governance variables (NDIR and IND). The association between corporate governance variables and bankruptcy runs in both directions. Thus, suggesting that the changes of bankruptcy status has an influence on SME corporate governance (NDIR and IND).

4.3.6 Artificial Neural Network Analysis of Nigerian Sample

The same multilayer perceptron (MLP) processes is applied to the Nigerian samples. All the networks used in this study have one hidden layer as it is deemed to be sufficient for MLP network (Ashiquzzaman *et al.*, 2017). For classification problems, the number of input nodes is the number of predictor variables which can be specified by the particular application. For example, there are 25 predictor variables in this study that are used to develop the three models for failure prediction of Nigerian SMEs. The networks input nodes in the first layer corresponding to the predictor variables used in each model.

Table 4.33
Artificial Neural Network of Nigerian Sample

Variables	Model 1			Model 2			Model 3		
	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior	3-year prior	2-year prior	1-year prior
	Weight	Weight	Weight	Weight	Weight	Weight	Weight	Weight	Weight
Constant									
EBIT	-5.298	4.108	-3.554				-1.077	-2.057	-0.221
ROE		1.163	-3.744				-0.334	-1.778	-0.891
TLA	4.405	-1.371	11.343				0.633		0.866
LTA	3.372						0.002		0.296
CLE							0.156	1.172	
LQT	-1.298	1.745					-0.604	-1.321	-0.592
WCT	-0.930		-2.375						
NWC							-0.271	-0.881	
EXP		-0.725	4.396				0.208		1.345
AST		2.413	-6.134				-0.359		
LogCAP			4.122						
LogTA	-1.387	-2.179	-3.382					-1.122	
AGE	-1.926	3.773	-8.678				-0.359	-3.060	-1.266
BLC							0.289	-1.256	0.998
MDD						-2.340			
CONT				-0.769	4.327	8.958		4.159	-2.638
NDIR				-2.427	-6.054	2.234	-0.307	-1.535	
IND					-1.186		0.462		
GENDER				-0.396	2.526			2.377	
HAUSA						-2.030			
IGBO						-2.436			
EMPY				0.320	1.228				
CPI				0.469	-0.807			1.422	-0.234
GDP							0.092		
LNR						2.002			-0.593
No. Hidden Layer	1	1	1	1	1	1	1	1	1
SSE	11.58	40.91	9.88	11.22	7.54	2.89	7.29	11.17	2.07
MSE	0.056	0.082	0.092	0.149	0.107	0.146	0.059	0.073	0.245

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Return on equity (ROE), earnings before interest and tax to total asset (EBIT), total liabilities to total assets (TLA), long-term debt to total assets (LTA), current liabilities to total asset (CLA), current liabilities to total equity (CLE), current assets to current liabilities (LQT), working capital to total debt (WCT), net working capital (NWC), asset turnover (AST), selling, general and administrative expenses to sales (EXP), logarithm of total assets (LogTA) and logarithm of share capital (LogCAP), years of business (AGE), location of business (BLC), controlling shareholder (CONT), managing director duality (MDD), number of directors in the board (NDIR), board independence (IND), gender of managing director (GENDER), ethnicity of managing director as Hausa (HAUSA), ethnicity of managing director as Yoruba (YORUBA), ethnicity of managing director as Igbo (IGBO), ethnicity of managing director as Foreign (FOREIGN), gross domestic product (GDP), lending rate (LNR), consumer price index (CPI) and unemployment rate (EMPY). Sum of square Error (SSE), Mean Square Error (MSE).

Table 4.33 presents model summary and the significant variables with their weight selected based on their relative importance and contribution towards the output in each model through the aid of the Neural Interpretation Diagram (NID)³³ and Garson's algorithm method. More so, in each of the models developed, the variables are the same as the ones found to be significant predictors in SMEs bankruptcy prediction using the logistic regression technique.

The weights that connect variables in a neural network are partially analogous to parameter coefficients in a standard regression model and can be used to describe relationships between variables. Negative connection weights represent inhibitory effects on neurons (reducing the intensity of the incoming signal) and decrease the value of the predicted response, whereas positive connection weights represent excitatory effects on neurons (increasing the intensity of the incoming signal) and increase the value of the predicted response (Olden & Jackson, 2002).

Consistent with the logistic regression results, the debt ratios (TLA), profitability ratio (EBIT and ROE), liquidity ratio (LQT), age of the company (AGE), controlling

³³ The diagrammatic illustration of this study's results using this method can be viewed in appendix 5.

shareholder (CONT) and board size (NDIR) appeared in all the prior year samples. This shows how important the variables are in predicting bankruptcy among SMEs in Nigeria as they appeared in both logistic regression and ANN. Expense ratio (EXP), gender of MD and growth in inflation rate (CPI) also appeared in both methods but not in all the prior year's to bankruptcy samples.

The significant different among the predictors is on the macroeconomic variables where logistic regression identified unemployment rate to be the most significant predictor among the category. However, ANNs identified inflation rate appeared as the most significant and important predictor among the macroeconomic variables. The positive weight of CPI indicate that an increase inflation rate would likely cause bankruptcy among SMEs in Nigeria. Bhattacharjee, Higson, Holly and Kattuman (2002) and Millington (1994) reports a consistent finding on inflation rate.

MSE and SSE in table 4.33 clearly shows that model 3 which incorporate financial, non-financial, corporate governance and macroeconomic variables is a much better model than model 1 and model 2. The model 3's SSE is the least as compare to model 1 and model 2 with 7.29, 11.17 and 2.07 for the 3-year, 2-year and 1-year prior to bankruptcy sample respectively. Similarly, Model 3 scores the least error using MSE for the 2-year prior to bankruptcy sample with 0.073 while model 1 perform better for 3-year and 1-year prior to bankruptcy samples with 0.056 and 0.092 respectively. More so, as we move closer to bankruptcy, model 2 error reduced marginally.

4.3.7 Models Performance and Validation under ANN

Table 4.34 provides a summary of the classification rate of the models for the estimated and holdout sample. Model 1 has an accuracy rate of 96, 91.5 and 91 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively. The holdout sample for model 1 is having an accuracy rate of 91.4, 77.4 and 81.5 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples. Furthermore, model 2 accuracy rate of the estimated sample is 81, 94.2 and 86.6 percent for the respective 3-year, 2-year and 1-year prior to bankruptcy samples.

Table 4.34

ANN Classification rate for both estimated and holdout sample for Nigeria

	Estimated Sample (Training)			Holdout Sample (Validation)		
	3-year	2-year	1-year	3-year	2-year	1-year
Model 1	96.0%	91.5%	91.0%	91.4%	77.4%	81.5%
Model 2	81.0%	94.2%	86.6%	78.7%	82.4%	78.9%
Model 3	97.4%	97.8%	97.9%	90.4%	86.1%	86.2%
Observation	276	138	94	68	34	22

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. Observation represents number of SMEs in the analysis.

Besides, model 3 that combined both financial, non-financial, corporate governance and macroeconomic variables provides the highest predictive accuracy rate for both the estimated and holdout sample. The accuracy rate of the estimated sample is 97.4, 97.8 and 97.9 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively. The accuracy rate of the holdout sample is 90.4, 86.1 and 86.2 percent for the 3-year, 2-year and 1-year prior to bankruptcy samples respectively.

4.3.8 Comparison of Accuracy Rate Results of Nigerian Sample

This section compared the accuracy rate results of the three models developed in the study using logistic regression and artificial neural networks (ANN) methods. The comparison of the methods is performed on the basis of the overall accuracy rate of the models develop and type I and type II error rates. These results are presented in table 4.26 (for Logistic regression) and table 4.34 (for ANNs) and table 4.35 for the type I and type II error rate. As far as the overall correct classification is concerned, results in Table 4.34 indicate that the ANN provides the highest accuracy rate in majority of the models and the prior year samples.

Table 4.35

Misclassification rates of the different models for Nigeria

	Type I error rate			Type II error rate		
	3-Year	2-year	1-Year	3-Year	2-year	1-Year
Logistic Regression Approach						
Model 1	6.4%	15.1%	17.2%	7.6%	14%	12.1%
Model 2	19.8%	9.3%	6.9%	23.8%	14%	27.6%
Model 3	5.2%	4.7%	6.9%	3.5%	5.8%	6.9%
Artificial Neural Network Approach						
Model 1	2.2%	11.4%	9.5%	5.9%	5.6%	8.5%
Model 2	14.8%	4.6%	8.2%	22.7%	6.8%	18.8%
Model 3	2.9%	0%	2.1%	2.3%	4.4%	2.1%

Model 1: financial and non-financial variables, model 2: governance and macroeconomic variables, model 3: combined model 1 and 2. The overall misclassification error is estimated as the average of the type I and the type II error rates.

The results indicate that ANN is more robust and provide a higher overall accuracy rate for all the prior year to bankruptcy samples in model 1 than logit model (for the 3-year prior to bankruptcy sample, 96% vs 96%; for the 2-year prior to bankruptcy sample, 91.5% vs 85.6% and 1-year prior to bankruptcy sample, 91% vs 84%). The ANN accuracy rate for model 2 remains higher for the 3-year prior and 2-year prior

to bankruptcy sample (81% vs 78.9% and 94.2% vs 87.1% respectively) but logit model marginally achieved a higher accuracy rate in the 1-year prior to bankruptcy sample (87.2% vs 86.6%).

Furthermore, the result for model 3 also indicates that ANN is more robust than logistic regression in estimating the overall accuracy rates across the three year prior samples. This can be seen from the overall accuracy rate for the 3-year prior to bankruptcy sample (97.4% vs 97.1%), 2-year prior to bankruptcy sample (97.8% vs 95.7%) and 1-year prior to bankruptcy sample (97.8% vs 93.1%). Similar trend is also found in the holdout sample where ANN accuracy rates outperformed that of logistic regression except for model 1's 2-year prior and 1-year prior to bankruptcy samples (81.8% vs 77.4% and 81.8% vs 81.5% respectively) where logistic regression performed better.

Furthermore, in order to compare the performance between the two methods, the study also assess the accuracy rate of each model in correctly classifying bankrupt and non-bankrupt SMEs, using the type I and type II error rates. The type I error refers to the classification of bankrupt SMEs as non-bankrupt whereas the type II error refers to the classification of non-bankrupt SMEs as bankrupt. The ANN method outperforms logistic regression method in all the prior year's sample in terms of the overall error rate i.e. having a lower error rate. Most notably, the type I and type II error rate reduced significantly in model 3 for both ANN model and logit model but ANN being more superior.

The finding of this study are consistent with previous studies where the application of neural networks in many bankruptcy prediction studies has been reported to outperform conventional statistical methods among which is logistic regression (Ciampi et al., 2009; Neophytou et al., 2001; Park, 2005; Shin & Lee, 2002; Zhang et al., 1999). In summary, comparing the overall accuracy rate results of the ANN and logistic regression models developed in this study, conclusion can be made that ANN models are considered the most reliable for predicting SMEs bankruptcy in Nigeria.

4.3.9 Summary of the Research Hypothesis of Nigerian Sample

The objective of this study is to develop bankruptcy prediction models among SMEs using financial, non-financial, corporate governance and macroeconomic variables. The finding were presented in the previous sections and the summary of the relations found between each of the independent variables and bankruptcy of SMEs in Nigeria are as follows:

Table 4.36

The summary of the hypothesis and the finding – the relationship between the financial, non-financial, corporate governance and macroeconomic indicators and SMEs bankruptcy.

Hypotheses	H. Sign	A. Sign	Sig.	Conclusion
<i>H1: There is a negative relationship between profitability and bankruptcy.</i>	-	-	Sig. (1%)	Supported
<i>H2: There is a positive relationship between leverage and bankruptcy.</i>	+	+	Sig. (1%)	Supported
<i>H3: There is a negative relationship between liquidity and bankruptcy.</i>	-	-	Sig. (5%)	Supported
<i>H4a: There is a negative relationship between activity ratios (asset turnover) and bankruptcy.</i>	-	-	Sig. (5%)	Supported

Hypotheses	H. Sign	A. Sign	Sig.	Conclusion
<i>H4b: There is a positive relationship between activity ratio (expense ratio) and bankruptcy.</i>	+	+	Sig. (5%)	Supported
<i>H5: There is a relationship between size of SME and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H6: There is a relationship between business location and bankruptcy.</i>	+/-	-	Sig. (5%)	Supported
<i>H7: There is a negative relationship between age of SME and bankruptcy.</i>	-	-	Sig. (1%)	Supported
<i>H8: There is a relationship between CEO duality and bankruptcy.</i>	+/-	+		Not Supported
<i>H9: There is a relationship between board size and bankruptcy.</i>	+/-	-	Sig. (5%)	Supported
<i>H10: There is a relationship between controlling shareholder and bankruptcy.</i>	+/-	+	Sig. (1%)	Supported
<i>H11: There is a negative relationship between independent director and bankruptcy.</i>	-	-	Sig. (5%)	Supported
<i>H12: There is a relationship between gender of managing director and bankruptcy.</i>	+/-	+/-	Sig. (5%)	Supported
<i>H13: There is a relationship between ethnicity of managing director (HAUSA and FOREIGN) and bankruptcy.</i>	+/-	+	Sig. (5%)	Supported
<i>H14: There is a negative relationship between GDP and bankruptcy.</i>	-	-		Not supported
<i>H15: There is a positive relationship between unemployment and bankruptcy.</i>	+	+	Sig. (5%)	Supported
<i>H16: There is a positive relationship between inflation rate and bankruptcy.</i>	+	+	Sig. (10%)	Supported
<i>H17: There is a positive relationship between interest rate and bankruptcy.</i>	+	-	Sig. (5%)	Not Supported

Note: H= Hypothesised, A= Actual, Sig.= Significance

4.4 Comparison of Significant Predictors of SMEs Bankruptcy between Malaysia and Nigeria

As discussed in chapter 1, the Malaysian and Nigerian government through their central banks signed a memorandum of understanding (MOU). The MOU is to allow Malaysia to share expertise and exchange relevant information in the areas of SMEs development and policies to Nigeria. This includes stimulation of economic development through financing SMEs, effective supervisory framework, increasing productivity, innovation and technology sharing to strengthen the long term competitiveness of the SMEs in Nigeria (Central Bank of Nigeria, 2010). This strategic partnership provides a natural platform for this study to compare the significant predictors of SMEs bankruptcy between Malaysia and Nigeria. The comparison is to identify the similarities and differences based on the models developed in the study (model 1, model 2 and model 3).

On the part of financial indicators, profitability, leverage, liquidity and activity ratios are significant variables for both Malaysia and Nigeria. Furthermore, among the non-financial variables, age and business location of SMEs are significant variables in predicting business bankruptcy in Malaysia and Nigeria. The results show that higher profitability lower the likelihood of bankruptcy among SMEs in both countries. With high level of profit, SMEs would be able to retain more of their profit and used it as a major source of finance for future growth and development (Myers, 1984). Pecking order theory application to SMEs would relate more to retain earnings and debt finance. This is because majority of the SMEs managers tend to be the business owners and they do not normally want to dilute their ownership claim.

Therefore, the theory's application to SMEs implies that external equity finance issues may be less preparable for the owners of SMEs (Zoppa & McMahon, 2002).

Financial leverage is another determinant of SMEs survival in Malaysia and Nigeria. Total debt liabilities measured by total debt to total assets (TLA) found to be the key measure of leverage. Debt financing is cheaper than equity financing but high level of leverage will result in higher probability of bankruptcy. SMEs financing channels are limited. SMEs depend on debt financing from financial institutions or capital from the owners. A company with high level of debt has a greater percentage of fixed costs to its total costs. In good times this is less of a concern, but in bad times it can become increasingly difficult for businesses to make scheduled interest and principal payments. The result also supports the trade-off theory (Hirshleifer, 1966; Robichek & Myers, 1965). Therefore, SMEs in Malaysia and Nigeria should maintain a healthy level of leverage especially when the company is faced with volatile cash flows.

SMEs in Malaysia and Nigeria should also pay attention to their firms' liquidity due to their dependence on debt financing. A company may likely to go into financial distress if it fails to fulfil its short term commitments and obligations. Liquidity measured by current asset to current liabilities (LQT) and working capital to total debt (WCT) are the significant measures of business bankruptcy among SMEs in Nigeria while LQT, WCT and net working capital (NWC) are the significant measures of liquidity among the Malaysian SMEs. The higher the ratio, the more quicker and easy a company could liquidate its liquid assets to fulfil its short term

obligations, which is a sign of good financial health. Sufficient level of liquidity is likely to reduce the probability of bankruptcy among SMEs in both countries.

Due to the intense competitive business environment and the fight for large market share among businesses, operational efficiency is critical to the SMEs survival. The asset turnover ratio indicates the amount of revenues, or sales, a company generates for each dollar invested in assets. In order for the company to be effective and efficient, those assets must be fully utilised to generate sales revenue. The asset turnover ratio is an important asset management ratio because it helps companies to assess how efficient are they in using the companies' assets. A higher ratio is indicative of greater efficiency in managing asset, and how fast a company is able to generate sales through the use of its assets. This ratio is significant predictor of SMEs bankruptcy in Malaysia and Nigeria. There is a need to improve asset efficiency of SMEs in both countries to reduce the likelihood of bankruptcy. Furthermore, in the case of Nigeria, expense ratio is also a significant measure among the efficiency ratios. When the ratio is high, it shows that managers are not efficient in controlling organisational costs (Anderson et al. 2007). Therefore, SMEs in Malaysia and Nigeria have to increase their efficiency in utilising their assets to generate sales revenue and control cost in order to increase profitability and ultimately reducing the probability of business bankruptcy.

Furthermore, age of SMEs is a significant predictor of bankruptcy in Malaysia and Nigeria. Older SMEs are less likely to fail as they are more able to discover their strength in the market and take advantage of it (what they are good at and learn how to do things better). They are able to specialize and find ways to standardize,

coordinate, and speed up their production processes, as well as to reduce costs and improve quality (Arrow, 1962; Jovanovic, 1982; Ericson & Pakes, 1995). In return, the SMEs are expected to be more profitable because of several strategic or operational reasons. This includes the ability to tap into the relevant customer segment and provide differentiated products that meet demand which will help them in gaining customer loyalty and build up better rapport with suppliers (Majumdar, 1997). This can reduce the probability bankruptcy. Moreover, business location of SME is also a significant predictor of bankruptcy in both countries. SMEs in less industrialise state will faced higher probability of bankruptcy due to less economic activities, lack of infrastructural development and high uncertainty in business dealings compared to SMEs in more industrialised states.

Corporate governance predictors such as controlling shareholder, number of directors on SMEs board and gender of managing directors are significant predictors in Malaysia and Nigeria. The results from both countries prove that high degree of ownership concentration creates high probability of business bankruptcy as controlling shareholders tend to exercise their control rights to generate private benefits at the expense of the minority shareholders. The finding supports the advocate of agency theory where they believe that if ownership concentration exceed some limits, it will have negative impact on the firm performance (Jensen & Meckling, 1976; Shleifer & Vishny, 1986).

Board size is found to have a negative coefficient in Malaysia and Nigeria, suggesting that larger board size reduces the probability of SMEs bankruptcy. Company with a larger board have access to diverse skills, expertise and experience

from different members to help monitor the CEO effectively and increase monitoring function (Eisenberg, Sundgren, & Wells, 1998). Furthermore, the corporate governance code in both countries recommends that the board should be of a sufficient size relative to the scale and complexity of the company's operations and be composed in such a way as to ensure diversity of experience without compromising independence, compatibility, integrity and availability of members to attend meetings (MCCG, 2017; NCCG, 2016).

The presence of independent directors in Nigerian SME's board reduces the probability of bankruptcy as the variable is negative and significant in model 2 (3-year prior to bankruptcy sample) and model 3 (3-year prior to bankruptcy sample). Independent directors bring independent and objective judgment to the board and this lessens risks arising from conflict of interest or undue influence from interested parties. However, the variable is positive and only significant in model 3 (3-year prior to bankruptcy sample) in Malaysian context. This may suggest that the SMEs executive directors are more aware and have better knowledge about the business operations compared to independent directors. This finding suggests that when the cost of having independent director outweigh the benefit of having them on board it could lead to bankruptcy.

Managing director duality increases the probability of SMEs bankruptcy in Malaysia. The finding is in support of the agency theory that argues that the CEO and chairman should be separated to bring good governance practice on board. Additionally, the finding shows that SMEs are not following the MCCG (2017) recommendations that the positions of chairman and CEO should be held by

different individuals to promote accountability. The variables are not a significant predictor of SMEs bankruptcy in Nigeria.

Moreover, macroeconomic variables in both countries do not play a very significant role in predicting SMEs business bankruptcy. The economic variables are less influential in the bankruptcy prediction models. Unemployment rate is the only significant variable for Malaysian data set for model 2 (3-year and 2-years prior to bankruptcy samples). However, for Nigeria, the unemployment rate is significant in model 2 (2-year prior to bankruptcy sample) and model 3 (3-year and 1-year prior to bankruptcy samples). Moreover, inflation rate and interest rate are among the significant predictors of SME bankruptcy in Nigeria.

The results from Malaysia and Nigeria show that among the models, model 3 have the highest performance in terms of highest predictive accuracy rate for both estimated and holdout sample as the model combined financial, non-financial, corporate governance and macroeconomic variables. Additionally, for the Nigerian samples, the results reveal that as the bankruptcy event approaches (2-year and 1-year prior to bankruptcy samples), the performance or the accuracy rate of the estimated and holdout samples decreases. Therefore, the 3-year prior to bankruptcy sample has the highest accuracy rate compared to the 2-year and 1-year prior to bankruptcy samples. For Malaysia, the finding shows that the models predict bankruptcy more accurately as bankruptcy event approaches especially in the 2-year prior to bankruptcy sample. The 2-year prior to bankruptcy sample has the highest performance or highest accuracy rate in the models compared to the 3-year and 1-year prior to bankruptcy samples.

Furthermore, the results from Malaysia and Nigeria show that bankruptcy prediction models developed using the ANN method yield higher predictive accuracy rate compared to models developed using the logistic regression. ANN is more robust, accurate and provides higher overall classification rates in the three different observations prior samples compared to the logistic regression method. The finding suggests that forecasting with ANN is more reliable for business bankruptcy prediction models.

4.5 Chapter Summary

This chapter presents the empirical finding regarding the effect of financial, non-financial, corporate governance and macroeconomic variables on SMEs bankruptcy. Specifically, the chapter attempted to achieve three main objectives. Firstly, it attempted to examine whether financial, non-financial, corporate governance and macroeconomic variables have significant impact on SMEs bankruptcy in Malaysia and Nigeria together with a number of descriptive statistics. For Malaysia, the finding from logistic and ANN method show that financial variables such as profitability (ROE), leverage (TLA and CTA), liquidity (LQT and WCT), and efficiency ratio (EXP and LogCAP) are significant predictors of SMEs bankruptcy. A similar result is observed for the Nigerian data where profitability (EBIT), leverage (TLA and CLE), liquidity (LQT and WCT), and efficiency ratio (EXP and LogTA) are also among the financial variables that significantly predict bankruptcy among SMEs.

Furthermore, among the non-financial variables, age and business location of an SME are significant predictors of bankruptcy in both Malaysia and Nigeria. On the

part of corporate governance variables, managing director duality, ethnicity of managing director, controlling shareholder, number of directors on board and gender of managing director are the most significant predictors of SMEs bankruptcy in Malaysia and Nigeria. For the later, the presence of independent director is also found to be a significant predictor. Macroeconomic variables have less impact on SMEs bankruptcy in both countries. In Nigeria unemployment rate, inflation rate and interest rate are among the significant predictors of SME bankruptcy while in Malaysia only unemployment rate is found to be significant. Furthermore, an examination on the problem of endogeneity for the specific governance variables shows that the results are robust to 2SLS regression specifications.

Secondly, the chapter compared the consistency of the business failure prediction models developed using different statistical techniques for the SMEs in Malaysia and Nigeria. The finding show that in each of the models developed, using either the logistic regression or ANN, the significant predictors of SME bankruptcy are almost similar to Malaysia and Nigeria. Thirdly, the chapter compared the empirical strengths of the two methods (i.e. logistic regression and ANN) by examining the overall predictive accuracy rate of the estimated and holdout samples. In addition, the type I and type II error rate of the models were compared between the two methods. As far as the overall classification rate is concerned, results from Malaysia and Nigeria indicate that the ANN provides the highest accuracy rate in majority of the models developed and the prior year to bankruptcy samples both in the estimated and holdout analysis. Furthermore, comparing the type I and type II error rate results show that ANN models provides the least error and are more robust and are considered the most reliable in predicting SMEs bankruptcy in Nigeria and Malaysia.

CHAPTER 5

CONCLUSION

5.1 Introduction

This final chapter presents the summary of the empirical investigations that predict bankruptcy among SMEs in Malaysia and Nigeria using financial, non-financial, governance and macroeconomic variables. The chapter also discusses the implications and limitations of the investigations, as well as suggestions for future research.

5.2 Summary of the Finding

Issues relating to SMEs and bankruptcy prediction have been the focus of many scholarly and regulatory debates around the world. This is as a result of SMEs significant role towards economic development and sustainability. There are generally two issues in relation to business bankruptcy prediction. The first is a search for a set of explanatory variables that efficiently predict and explain business bankruptcy. Majority of the previous studies have circled around the use of financial and non-financial variables in predicting business bankruptcy among SMEs, but only a limited number of studies have incorporated corporate governance and macroeconomic variables in the prediction model. The second is a search for an efficient empirical method to predict SMEs business bankruptcy. Previous studies have predominantly sought evidence from developed countries with little evidence from developing countries like Nigeria and Malaysia where the markets are different in terms of regulations and structure.

This study has determined the financial, non-financial variables, corporate governance and macroeconomic variables to predict and to explain the bankruptcy of the Malaysian and Nigerian SMEs for the prediction periods, 3-year, 2-year and 1-year prior to bankruptcy. The analysis has covered a sample observation consisting of 1,556 SMEs (778 SMEs are bankrupt SMEs based on Court orders and Creditors requests) for Malaysia and 632 SMEs (316 are bankrupt SMEs based on Court orders) for Nigeria from 2000 to 2014. This study contributes to the SME literature in various ways. It presents additional empirical finding on predicting business bankruptcy among SMEs in the manufacturing sector in Malaysia and Nigeria. It also explores a more comprehensive variables by incorporating financial, non-financial, corporate governance and macroeconomic variables to the prediction model. By incorporating these four categories of variables in a single model, it has significantly improved performance i.e. the prediction accuracy rate. For instance, model 3 from the Malaysian (Nigerian) sample that combines the four categories of variables to predict SMEs bankruptcy improves the prediction accuracy by 4.1 (9) percent from the benchmark model, model 1. Therefore, the finding confirm that using corporate governance and macroeconomic variables as additional predictors of business bankruptcy can improve the prediction accuracy rate of the models.

The prediction analysis using the Malaysian SMEs shows that among the financial variables, profitability (ROE), leverage (TLA) and liquidity ratios (LQT) are found to be significant predictors. The finding indicates that a higher level of profitability lowers the probability of bankruptcy. This will assist the SMEs to retain some of the profits and reinvest to further strengthen the growth of the company through expansion without relying on external sources that are costly. Furthermore, the

companies would be able to hire competent and skilful employees who can handle the growing responsibilities of the SMEs. Additionally, the finding shows that high level of debt leads to SMEs bankruptcy. SMEs with high amount of debt financing would face high financial risk that increases the probability of bankruptcy. Moreover, the finding also reveal that insolvency increases the risk of firms failing to meet short term commitments and obligations, which is likely to cause bankruptcy. For the non-financial variables, age and business location of SMEs are significant predictors. The longer the existence of an SME, the higher the chance of its survival. This is because SMEs will have vast experience and management capabilities (expertise) that develop over time. In addition, SMEs located in more industrialised states, such as Selangor, Kuala Lumpur, Johor, Sarawak and Pulau Pinang in Malaysia are less likely to go bankrupt. This is because industrialised states can provide competitive advantages, such as easy access to proactive business networks, which would also include having good rapport with customers, suppliers, industry and government agencies, due to close proximity. However, the finding also shows that SMEs in more industrialised state are likely to go bankrupt. This could be that SMEs located in more industrialised states are more likely to face competition from other SMEs as well as larger corporation and multinational companies. Industrialised states attract more industry players, which makes the competition more intense in those areas.

The number of directors, managing director duality, controlling shareholders, ethnicity and gender of managing directors are among the significant corporate governance variables. The findings suggest that a larger board can decrease the probability of bankruptcy among SMEs, because they would have access to diverse

skills and experience from different members and be able to monitor the managing director effectively on matters such as investment opportunities and business efficiency among others. An SME with a managing director who is also the chairman of the board is more likely to go bankrupt because this could lead to a more controlling management, where the impartiality of the board is compromised, less monitoring and control and an over-concentration of decision-taking functions.

Furthermore, the greater the holding of the controlling shareholder, the higher is the likelihood of bankruptcy among SMEs. The controlling shareholder may interfere in the activities of the board which could be an obstacle for managerial initiative. Since they have the power to appoint and to dismisses board members, they can also exert pressure on directors to act in their favour and influence their decision at the expense of minority shareholders. In addition, SMEs managed by men are more likely to go bankrupt compared to the female counterpart. Women managing directors are more likely to make conservative decisions than men, and therefore, are more risk averse. As a result, their firms' risk level should be lower than firms managed by a male, thus, reducing the probability of bankruptcy. Additionally, SMEs managed by the Malay or Chinese managing directors are more likely to go bankrupt compared to SMEs managed by foreign managing directors. Malays have a high uncertainty avoidance which reflects their uneasiness in dealing with ambiguities and uncertainty. As a result, they might also be losing out on business opportunities that could help the company to grow further in the future which could result in bankruptcy. On the other hand, the Chinese are rated as having a low uncertainty avoidance, individualistic, willing to accept new challenges and willing to take

greater risk. SMEs managed by the Chinese would therefore, probably face more risk that could lead to bankruptcy.

In Nigeria, the financial ratios such as profitability (EBIT) and leverage (TLA) are among the variables that are found to be significant predictors of SMEs bankruptcy. SMEs with huge debt liabilities are likely to go bankrupt due to the high level of financial risk whereas profitable SMEs face lower bankruptcy risk because of their higher performance. As for the non-financial variables, SME's age indicates that the longer the SME is in business, the less likely it is to fail. When firms become older, they become more transparent and are likely to gain access to cheaper debt financing given their well-established reputation and good relationship with creditors. Thus, older firm are less likely to go bankrupt. SMEs located in less industrialised states are relatively riskier and more likely to go bankrupt than their counterparts located in more industrialised states such as Abuja, Delta, Lagos, Kano and Rivers. This is because SMEs in less industrialised states are exposed to a high risk of uncertainty since they operate in a more difficult and uncertain economic environment. In addition, less industrialised states lack good infrastructure, market potential and have a less vibrant economic environment with fewer activities.

Moreover, among the corporate governance variables, the number of directors, controlling shareholders and independent directors are found to be significant predictors of SME bankruptcy. The presence of controlling shareholders is likely to trigger bankruptcy among SMEs because they tend to use corporate resources for their own interests by expropriating the interest of other shareholders and stakeholders. Moreover, a large board size can decrease the probability of SMEs

bankruptcy as a result of an increase in monitoring activities of the managing director. In addition, a large board size would also mean that there are more resources and information that would assist the management in formulating strategies. The presence of independent directors in SMEs board is also likely to reduce business bankruptcy because they contribute effective monitoring and serve as a disciplining tool for managers. On the other hand, high unemployment rate is associated with SMEs bankruptcy. During this business cycle, businesses experience a fall in consumer demand and many investment projects are not making money. Orders will be cut, inventory levels will be reduced and business failures will occur as firms find themselves unable to sell their goods.

Accordingly, the comparison between Malaysia and Nigeria affirms that SMEs in both countries finance most of their business operations using debt as they have limited access to capital market. The result also shows that profitability is negatively related to bankruptcy and bankrupt SMEs are less profitable compared to non-bankrupt SMEs. Similarly, SMEs with lower liquidity are more exposed to business bankruptcy. SMEs located in less industrialized states of Malaysia and Nigeria are more prone to business bankruptcy. Young SMEs are more likely to fail compared to longer existing SMEs due to experience and growth development.

Furthermore, the comparison shows that most of the bankrupt SMEs in Malaysia and Nigeria have a controlling shareholders. Non-bankrupt SMEs have more directors in their boardroom who can help to monitoring and to share expertise in the company's operations while bankrupt SMEs have fewer directors. Independent director is also a significant predictor of SMEs bankruptcy in Malaysia and Nigeria, while managing

director duality is only a significant predictor of SMEs bankruptcy in Malaysia. Macroeconomic variables in both countries do not play a significant role in predicting SMEs bankruptcy, except for unemployment rate which is significant to predict bankruptcy among SMEs in Malaysia and Nigeria. This economic variables is positively related to SMEs bankruptcy.

Moreover, the results from Malaysia and Nigeria show that the bankruptcy prediction models developed using the ANN method yield a higher predictive accuracy rate compared to models developed using the logistic regression method. ANN is more robust, accurate and provides higher overall classification rates in all the sub-samples. The finding suggests that forecasting with ANN is more reliable for business bankruptcy prediction models.

5.3 Implications of the Study

The finding of this study should be of potential interest to the management of SMEs, financial institutions, policy makers, trade creditors and academics. In order to improve the SMEs' ability to successfully face the complex challenges of a competitive business environment, bankruptcy prediction model could be used to guide managerial action in order to identify the significant factors that are likely to cause potential bankruptcy for their companies. The finding of this could study assist the management of SMEs to understand the financial ratios that have the likelihood of putting their firm into potential bankruptcy. This will assist the management to take timely solutions that would enable the SMEs to develop viable financial strategies to avoid going bankrupt. For example, SMEs should reduce their exposure to debt as the finding indicates that a high level of debt financing would increase the

probability of bankruptcy among SMEs. Moreover, the management of SMEs should improve operating efficiency in terms of asset utilisation, waste reduction in the manufacturing process and optimal production output so as they could generate enough cash flows to pay off debt.

To be successful and remain in business, SMEs need to increase their profitability as it is important for survival. The higher the profitability the lower the probability of going bankrupt. This could be observed in the finding of this study where SMEs with high profitability is found to use less debt financing. Accordingly, SMEs can enhance their firm's profitability depending on how efficiently they manage their working capital, as it could help improve firm's liquidity. A key concern for SMEs is working capital management. SMEs should have sufficient working capital to support their operation. Failure to do so would increase the firm's risk of failing to meet their financial commitment, which is likely to cause business bankruptcy. As such, the management of SMEs would need to continuously improve their managerial and accounting skills, to acquire necessary knowledge on appraising their performance and investments and to focus on the needs of proper internal accounting control systems.

Overall, the finding of this study would assist SMEs in detecting business bankruptcy as early as three, two and one-years before they fail. Therefore, the results of this study could serve as an early warning signal for management of SMEs to address and to take proactive measures such as improving the internal governance structure of the organisation to prevent potential bankruptcy. For example, SMEs should discourage CEO duality. A CEO should not be the chairman at the same time.

This is because it may lead to an increase of organisation's agency cost as management might pursue their own self-interest by forgoing an opportunity that may be in the best interest of the shareholders. It also leads to deterioration of the fiduciary oversight power of the board of directors resulting in poor checks and balances mechanism. Additionally, SMEs should enhance their governance practice by appointing independent directors in the boardroom to facilitate access to new competences, resources, and relationships with the outside world. Moreover, the finding suggests that SMEs should also reduce ownership concentration as controlling shareholder(s) are likely to cause business bankruptcy. They tend to exercise their control rights to generate private benefits and hire unqualified individuals related to them at the expense of the minority shareholders.

Financial institutions such as banks would also benefit from this study as the finding can be a reference model to set up their internal systems and procedures to manage credit risk of SMEs. Specifically, it would be helpful to the banks in assessing the credit risk of an SME. This study also highlights the usefulness of including corporate governance variables in the bank's credit-rating systems. Moreover, non-financial information, such as business location, can be rechecked frequently allowing banks to adjust their credit policy in a timely manner. Banks in Malaysia and Nigeria should therefore, consider the results of this study in their credit evaluation systems. Similarly, suppliers, who are also considered as close associates or trade creditors to SMEs, would also benefit from the finding of this study. The business bankruptcy prediction models developed in this study would provide additional information for these trade creditors to help them understand the going concerns of the SMEs and to decide on their credit policy.

The Malaysian and Nigerian governments recognise the important contribution of SMEs to their economies and domestic employments which is why resources are allocated each year to support the development of SMEs. The bankruptcy prediction models developed in this study could be a reference model for regulatory bodies, such as the National SME Development Council and SMEDAN, to formulate strategies for SME development, including their evaluation and monitoring policy. This would help them to closely assess the well-being of SMEs before deciding on any form of assistance towards their sustainability and continuous development. This could be achieved by adopting some relevant criteria such as profitability, leverage, operational efficiency and governance settings in formulation the strategies for SMEs. For example, the finding from this study would help policymakers to easily assess the SME and identify potentially distressed SMEs and provide them with the necessary assistance to avoid from going bankrupt. Professional advice can also be provided to improve the SMEs financial management and financial planning skills.

This study can also help policymakers to further understand and highlight the importance of governance practices among SMEs in both countries. For example, SMEs in Malaysia should be encouraged to comply to the principles and recommendations of the Malaysian Code On Corporate Governance (MCCG) 2017 and practice good governance as an integral part of their business dealings and culture. Similarly in Nigeria, SMEs should be encouraged to comply with the National Code of Corporate Governance (NCCG) 2016 recommendations on good governance structure and processes. The use of macroeconomic variables in this study would also help policymakers to further understand the external causes of business bankruptcy so that related parties could formulate policies to better serve

the business sector. This can be in the form of tax cuts or tax incentives to SMEs as well as reforms to ease the process of doing business. SMEs in less industrialised states in Malaysia and Nigeria are more prone to bankruptcy, as such the government of each country may further enhance the infrastructural deficit in those parts of their country that lead to high rates of SME bankruptcy.

5.4 Limitations of the Study

While the research finding are important, like any other empirical research, it may be subject to some limitations that need to be acknowledged. Financial and other information on SMEs is easily accessible in developed countries where there are numerous databases providing information on them either through government or private corporation databases (information provider or credit rating agencies). However, information on SMEs in developing countries such as Malaysia and Nigeria is limited to government agencies databases as SMEs are not required to make their financial accounts publicly available. Therefore, the data collected is limited to those available from the CCM and CAC databases. These databases do not cover a wide range of financial, non-financial or corporate governance variables that were found to be significant variables in previous studies. In addition, many companies have had to be dropped from the estimated sample due to missing data that further reduced the sample size. For example in Malaysia, there are 1,284 SMEs that went bankrupt during the observation period, but only 778 SMEs are included in the study due to limited availability of data. Similarly, in Nigeria, 630 SMEs went bankrupt during the observation period, but only 316 SMEs are included in the final sample.

Furthermore, the results should be interpreted with caution and not extended beyond the focused context provided here. The main focus of this study is the manufacturing sector given their significant contribution towards the economic development of Malaysia and Nigeria. Therefore, the finding of this study may not be directly applicable to SMEs in other sectors of the economy, although they can be used as a guide or reference model. This is because each sector is unique in terms of business nature, market segments and characteristics, risk profile, ownership structure, industrial and regulation structure and stakeholders. These differences could influence those variables that can predict the likelihood of SME's survival and as a result may potentially affect the accuracy and performance of the bankruptcy prediction model developed in this study.

Another limitation of this study is on the use of ANN method. Though the method provides the highest performance in terms of predictive accuracy rate compared to logistic regression, it suffers from problem of explanation capability or known as the black box nature of neural networks. Neural networks do not present explanation on learning process from input data to output compared to statistical methods (Mackinnon & Glick, 1999; Meyer, Balemi & Wearing, 2000; Kumar & Thakur, 2012; Tzeng, 2005).

5.5 Recommendations for Future Research

In view of the finding of this study and the limitations mentioned above, some areas which may be considered for future research are highlighted. Looking at the limited number of research incorporating governance variables among SMEs in predicting bankruptcy, more investigation should be carried out using SMEs from other sectors

of the Malaysian and Nigerian market. Each sector has its own unique characteristics, governance setting and different risk profile that attracts different types of stakeholders. Therefore, industrial effects, including regulation and competition, should be explored to add more value to the bankruptcy prediction literature.

In addition, cross country studies may be conducted between Malaysia and other countries as well as between Nigeria and other countries with high bankruptcy rates. This could be done using the same set of predictors used in this study in order to see how the effects of financial, non-financial, corporate governance and macroeconomic variables on SMEs survival can be applied to other national and international economic environments. This type of cross country analysis could also help to identify country specific variables that contribute to the bankruptcy of SMEs in those countries.

Moreover, the presence of type I and type II errors suggests the need to increase the number of independent variables used for SME bankruptcy prediction modelling, so as to include a high number of characteristics, particularly qualitative characteristics (through an interview, focus group discussion or questionnaire), that are related to the SMEs organisational structure (such as company profile, product information, internal control mechanism, stakeholders information, human resources, social and legal information and environmental information, among others) and industrial competitiveness (such as the level of technological readiness, innovation and creativity, value chain activities and bargaining power of suppliers and customers, among others).

REFERENCES

- Abdullah, N., Ahmad, A., Ahmad, H., & Md. Rus, R. (2008). Predicting corporate failure of Malaysia's listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model, *International Research Journal of Finance & Economics*, 15, 201-217.
- Abdullah, N., Ahmad, A., Md. Rus, R., & Zainudin, N. (2014). Modelling small business failures in Malaysia. Available at SSRN: <http://ssrn.com/abstract=2402129> or <http://dx.doi.org/10.2139/ssrn.2402129>
- Abdullah, M., Ma'aji, M., & Khaw-Lee, H. (2016). The value of governance variables in predicting financial distress among small and medium-sized enterprises in Malaysia. *Asian Academy of Management Journal of Accounting & Finance*, 12(1), 77-91.
- Abor, J., & Biekpe, N. (2007). Corporate governance, ownership structure and performance of SMEs in Ghana: implications for financing opportunities, *Corporate Governance*, 7(3), 288-300.
- ACCA (2013). The growth challenge, *Association of Chartered Certified Accountants, ACCA*.
- Agarwal, V. & Taffler, R. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? *Accounting and Business Research*, 37(4), 285-300.
- Agrawal, A., & Knoeber, R. (1996). Firm performance and mechanisms to control agency problems between managers and shareholders. *The Journal of Financial and Quantitative Analysis*, 31(3), 377-397
- Ahmad, A., Mohd, N., Rizal, A., & Marzuki, A. (2008). Macroeconomic Determinants of Corporate Failures in Malaysia, *International Journal of Business and Management*, 3(3) 3-10.
- Ahmad, N., & Seet, P. (2009). Dissecting behaviours associated with business failure: A qualitative study of SME owners in Malaysia and Australia. *Asian Social Science*. 5(9), 98–104.

- Ali, S., Liu, B., & Su, J. (2014). Does corporate governance quality reduce financial distress? New panel evidence from Australia. Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2481892
- Alifiah, M., Salamudin, N., & Ahmad, I. (2013). Prediction of financial distress companies in the consumer products sector in Malaysia. *Jurnal Teknologi*, 64(1), 85-91.
- Alifiah, M., Salamudin, N., & Ahmad, I. (2011). Revisiting financial distress prediction in the development sector in Malaysia, *Business Management Quarterly Review*, 2(2), 25-38.
- Alowaihan, A. (2004). Gender and business performance of Kuwaiti small firms: A comparative approach. *IJCM*, 14(3&4), 69-82.
- Altman, E. (1968). Financial ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, 23, 589-609.
- Altman, E., Marco, G., & Varetto, F. (1995). Corporate distressed diagnosis: comparisons using linear discriminant analysis and neural networks (The Italian experience). *Journal of Banking and Finance*, 18, 505 - 529.
- Altman, E., Edward, I., Haldeman, R., & Narayanan, P. (1977). A new model to identify bankruptcy risk of corporation. *Journal of Banking and Finance*, 1, 29–54.
- Altman, E., & Loris. B. (1976). A financial early warning system for over-the-counter broker dealers. *Journal of Finance*, 31(4), 1201-1217.
- Altman, E., Marco, G., & Varetto, F. (1994). Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (the Italian Experience). *Journal of Banking and Finance*, 18, 505-529.
- Altman, E., & Sabato, G. (2007). Modeling credit risk for SMEs: Evidence from US market. *A Journal of Accounting, Finance and Business Studies (ABACUS)*, 43(3), 332-357.

- Altman, E., Sabato, G., & Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. *Journal of Credit Risk*, 6(2), 95-127.
- Aoki, I., Komatsu, T., (1999). Analysis and prediction of the fluctuation of sardine abundance using a neural network. *Oceanol. Acta*, 20, 81–88.
- Aurelle, D., Lek, S., Giraudel, J.-L., Berrebi, P., (1999). Microsatellites and artificial neural networks: tools for the discrimination between natural and hatchery brown trout (*Salmo trutta*, L.) in Atlantic populations. *Ecol. Model.* 120, 313–324
- Akingbolu, R. (2010). Why 70% of SMEs fail in Nigeria? *This Day Live*, Retrieved May 16, 2015 <http://www.thisdaylive.com/articles/why-70-of-smes-fail-in-nigeria%20experts/71911/>
- Amran, N.A. (2011). The effect of owner's gender and age on firm performance: A review on Malaysian public listed family businesses. *Journal of Global Business and Economics*, 2(1), 104-116.
- Anderson, M. Banker, R., Huang, R., & Janakiraman, S. (2007). Cost behavior and fundamental analysis of SG&A costs. *Journal of Accounting, Auditing & Finance*, 22(1), 1-28.
- Aneta, P. & Anna, M. (2014). Default prediction for SME using discriminant and survival models, evidence from Polish market, *Quantitative Methods In Economics*, XV(2), 369–381.
- Anthony, B. (2005). Small and medium enterprises (SMEs) in Nigeria: problems and prospects, PhD Dissertation, ST. Clements University.
- Anthony, E. (2014). The role of SME firm performance in Nigeria, *Arabian Journal of Business and Management Review*, 3(12), 33-47.
- Anthony, E. & Harry, E. (2014). SME firms performance in Nigeria: Competitive advantage and its impact, *International Journal of Research Studies in Management*, 3(2), 75 - 86.

- Argenti, J. (1976). Corporate planning and corporate collapse, *Long Range Planning*, 9(6), 12–17.
- Argenti, J. (1986). Predicting corporate failure. *Accountancy*, 97(112), 157–158.
- Arrow, K. (1962). The economic implications of learning by doing. *American Economic Review*, 29, 155-173.
- Arslan, Ö. & Karan, M. (2009). Credit Risks and internationalization of SMEs. *Journal of Business Economics and Management*, 10(4), 361-368.
- Ashiquzzaman, A., Tushar, K., Islam, M., & Kim, M. (2017). Reduction of overfitting in diabetes prediction using deep learning neural network. arXiv preprint arXiv:1707.08386, 2017.
- Ayyagari, M., Demirgüç-Kunt, A. & Maksimovic, V. (2011). Small vs. young firms across the world – Contribution to employment, job creation, and growth, *Policy Research Working Paper 5631* (The World Bank Development Research Group).
- Aziz, M. A. and Dar, H. A. (2006). Predicting corporate bankruptcy: Where we stand? *Corporate Governance*, 6(1), 18–33.
- Azoff, E. M. (1994). *Neural network time series forecasting of financial markets*, Wiley, Chichester, NY.
- Back, B., Sere, K., & Vanharanta, H. (1996). Data mining accounting numbers using self-organizing maps, *Proceedings of STeP'96, Finnish Artificial Intelligence Conference*, Finnish Artificial Intelligence Society, Vaasa, Finland.
- Balcaen, S. & Ooghe, H. (2004). 35 years of studies on business failure: An overview of the classical statistical methodologies and their related problems, *Working Paper 2004/248*, Ghent University, Belgium.
- Barnes, P. (1987). The analysis and use of financial ratios: A review article. *Journal of Business Finance and Accounting*, 14(4), 449-461.

- Barber, B., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1), 261–292.
- Bart, C., & Bontis, N. (2003). Distinguishing between the board and management in company mission: Implications for corporate governance. *Journal of Intellectual Capital*, 4(3), 361–381.
- Bauer, J., & Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking & Finance*, 40, 432-442.
- Baum, C., Schaffer, M., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *Stata Journal*, 3, 1–31.
- Beale, R. & Jackson, T. (1990). *Neural Computing: An Introduction*, Hilger, Bristol
- Beaver, W. (1967). Financial ratios as predictor of failure, *Journal of Accounting Research*, 4, 71-111.
- Behr, P., & Guttler, A. (2007). Credit risk assessment and relationship lending: an empirical analysis of German small and medium-sized enterprises, *Journal of Small Business Management*, 45(2), 194-213.
- Bellovary, J., Giacomino, D. & Akers, M. (2007). A review of bankruptcy prediction studies: 1930-present. *Journal of Financial Education*, 33, 1-42.
- Bennett, R., & Smith, C. (2002). Competitive conditions, competitive advantage and the location of SMEs. *Journal of Small Business and Enterprise Development* 9(1), 73-86.
- Bhagat, S., & Bolton, B. (2008). Corporate governance and firm performance. *Journal of Corporate Finance*, 14, 257–273.
- Bhandari, S., & Weiss, A. (1996). *Corporate Bankruptcy: Economic and Legal Perspectives*, Cambridge University Press,
- Bhattacharjee A., Higson C., Holly S., & Kattuman P., (2002). Macro economic instability and business exit: Determinants of failures and acquisitions of large

UK firms. *Working Paper nr. 0206, Cambridge Working Papers in Economics, Department of Applied Economics, University of Cambridge* March 2002.

Biggins, J. V. (1999). Making board diversity work. *Corporate Board*, 20(117), 11–17.

Bilimoria, D., & Wheeler, J. (2000). Women corporate directors: Current research and future directions. In M. J. Davidson and R. J. Burke, (eds.). *Women in management. Current Research Issues*, II, 138 – 163.

Bismark, R. & Pasaribu, F. (2012). Capital structure and corporate failure prediction. *Journal of Economics and Business*, 5(3), 209-220.

Blanco, A., Irimia, A. & Oliver, M. (2007). The prediction of bankruptcy of small firms in the UK using logistic regression. *Análisis Financiero*, 118, 32-40.

Bliss, R., & Potter, M. (2002). Mutual Fund managers: Does gender matter? *Journal of Business and Economic Studies*, 8(1), 1–15.

Blum, M. (1974). Failing company discriminant analysis. *Journal of Accounting Research*, 12(1), 1-25.

Boritz, J., & Kennedy, D. (1995). Predicting corporate failure using a neural network approach. *Intelligent Systems in Accounting, Finance and Management*, 4(2), 95–111.

Börsch-Supan, A., & Köke, J. (2002). An applied econometricians' view of empirical corporate governance studies. *German Economic Review*, 3(3), 295-326.

Bozec, Y., & Laurin, C. (2008). Large shareholder entrenchment and performance: Empirical evidence from Canada. *Journal of Business Finance & Accounting*, 35(1-2), 25–49.

Bumgardner, M., Buehlmann, U., Schuler, A. & Crissey, J. (2011). Competitive actions of small firms in a declining market. *Journal of Small Business Management*, 49 (4), pp. 578-598.

Burke, R. J. (2003). Women on corporate boards of directors: The timing is right. *Women in Management Review*, 18(7), 364-368.

- Braunschweig, C. (2003). No business plans, please. *Venture Capital Journal*, 43(8), 24-31.
- Brickley, J., & James, C. (1987). The takeover market, corporate board composition, and ownership structure. *Journal of Law and Economics*, 30, 161-168.
- Brosse, S., Lek, S., Townsend, C. (2001). Abundance, diversity, and structure of freshwater invertebrates and fish communities: An artificial neural network approach. *New Zealand J. Mar. Fresh. Res*, 35, 135–145.
- Byrd, J., & Hickman, K. (1992). Do outside directors monitor managers? Evidence from tender offer bids. *Journal of Financial Economics*, 32, 195-207.
- Cadbury, A. (1992). *Report of the committee on the financial aspects of corporate governance*. Gee Publishing, London.
- Cadden, D. (1991). Neural networks and mathematics of chaos, *The First International Conference on AI Applications on Wall Street*, IEEE Computer Society Press, New York, NY, 52-7.
- Cant, C. & Wiid, A. (2013). Establishing the challenges affecting South African SMEs, *International Business & Economics Research Journal*, 12 (6), 707 – 716.
- Campbell, S. & Choudhury, A. (2005). The relationship between interest rates on the number of large and small business failures. *Academy of Accounting and Financial Studies Journal*, 9(3), 29-40.
- Cardone-Riportella, C. & Cazorla-Papis, L. (2001). New approaches to the analysis of the capital structure of SMEs: Empirical evidence from Spanish firms, Department de Economia de la Empresa, *Working Paper 01-10*, Business Economics Series 03.
- Central Bank of Nigeria (2014). Statistical bulletin 2014. Retrieved May 16, 2015 from <http://www.cenbank.org>
- Certo S., Richard, H., & Dalton, R. (2006). Top management teams, strategy and financial performance: A meta-analytic examination. *Journal of Management studies*, 43, 813-839.

- Chaganti, R., Mahajan, V., & Sharma, S. (1985). Corporate board size, composition and corporate failures in retailing industry, *Journal of Management Studies*, 22(4), 400–417.
- Chancharat, N. (2011). SMEs failure prediction: Literature review, *ABAC Journal*, 31(3), 70-81.
- Charalambous, C., Neophytou, E., & Charitou, A. (2004). Predicting corporate failure: empirical evidence for the UK. *European Accounting Review*, 13(3), 465-497.
- Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review*, Vol. 13, No. 3, 465 – 497.
- Chatfield, C. (1995). *Problem Solving: a Statistician's Guide*. Chapman & Hall, London
- Chava, S., & Jarrow, R. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, 8 (4), 537-569.
- Chen, D., & Ware, D. (1999). A neural network model for forecasting fish stock recruitment. *Can. J. Fish. Aquat. Sci.*, 56, 2385–2396.
- Chenhall, R. & Moers, F. (2007). The issue of endogeneity within theory-driven, quantitative management accounting research. *European Accounting Review*, 16(1), 173–195.
- Chirwa, E. (2008). Effects of gender on the performance of micro and small enterprises in Malawi. *Development Southern Africa*, 25 (3), 347–362.
- Chotima, S. (2013). SME manufacturing credit risk model forecast correctness and result of model. *IOSR Journal of Business and Management*, 11(4), 67-74.
- Ciampi, F., Vallini, C., & Gordini, N. (2009). Using artificial neural networks analysis for small enterprise default prediction modelling: statistical evidence from Italian Firms. *Oxford Business & Economics Conference Proceedings*. Oxford, 1, 1-26.

- Ciampi, F. (2015). Corporate governance characteristics and default prediction modelling for small enterprises. An empirical analysis of Italian firms, *Journal of Business Research*, 68, 1012–1025.
- Coada, A., Segarrab, A. & Teruel, M. (2013). Like milk or wine: Does firm performance improve with age? *Structural Change and Economic Dynamics*, 24(C), 173-189.
- Coates, P. & Fant, L. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management*, 142-155.
- Coleman, S., & Cohn, R. (1999). Small firm use of leverage: a comparison of man and woman-owned firms, *Conference Proceedings, United States Association of Small Business and Entrepreneurship*, San Diego, January 14-17.
- Collens, R. A., & Green, R. D. (1982). Statistical methods for bankruptcy forecasting. *Journal of Economics and Business*, 34(4), 349-354.
- Cooper, A., Gimeno-Gascon, F., & Woo, C. (1991). A resource-based prediction of new venture survival and growth. *Academy of Management Proceedings*, 113-119.
- Coughlan, A., & Schmidt, R. (1985). Executive compensation, managerial turnover, and firm performance: An empirical investigation. *Journal of Accounting and Economics*, 7, 43-66.
- Cornett, M., McNutt, J., & Tehranian, H. (2009). Earnings management at large US bank holding companies. *Journal of Corporate Finance*, 15, 412–30.
- Cressy, R (1992). UK small firm bankruptcy prediction: A logit analysis of financial trend, industry, and macro effects, *The Journal of Small Business Finance*, 1(3), 233-253.
- Cuba, R., DeCenzo, D., & Anish, A. (1983). Management practices of successful female business owners. *American Journal of Small Business*, 8(5), 40–46.
- Cuthbertson, K. & Hudson, J. (1996). The determinants of compulsory liquidations in the UK. *The Manchester School*, 64(3), 298–308.

- Cybenko, G. (1989). Approximation by superposition of a sigmoidal function. *Mathematics of Control, Signals and Systems*, 2, 303-314.
- Daily, C., & Dalton, D. (1994). Corporate governance and the bankrupt firm: An empirical assessment. *Strategic Management Journal*, 15(8), 643–654.
- Dalberg (2011). Report on support to SMEs in developing countries through financial intermediaries. *SME Briefing Paper, EIB Draft Version* (Geneva: European Investment Bank).
- Dalton, D., Daily, C., Johnson, J. & Ellstrand A. (1999). Number of directors and financial performance: A meta-analysis, *Academy of Management Journal*, 42, 674–686.
- Davis, J., Schoorman, F., & Donaldson, R. (1997). Toward a stewardship theory of management. *Academy of Management Review*, 22(1), 20-47.
- Davis, P., Babakus, E., Englis, P., & Pett, T. (2010). The influence of CEO gender on market orientation and performance in service small and medium sized service businesses. *Journal of Small Business Management*, 48(4), 475–496.
- Davis, E. (1995). *Debt, financial fragility, and systemic risk*, revised and expanded edition. New York, Oxford University Press.
- Davis, E., & Karim, D. (2008a). Comparing early warning systems for banking crises. *Journal of Financial Stability*, 4, 89—120.
- Davis, E., & Karim, D. (2008b). Could early warning systems have helped to predict the sub-prime crisis? *National Institute Economic Review*, 206, 35—47.
- Darayseh, M., Waples, E., & Tsoukalas, D. (2003). Corporate failure for manufacturing industries using firms specifics and economic environment with logit analysis. *Managerial Finance*, 29(8), 23-37.
- Deakin, E. (1972). A discriminant analysis of predictors of business failure, *Journal of Accounting Research*, 10(1), 167-179.
- Deakin, S., & Hughes, A. (1997). *Comparative corporate governance: An interdisciplinary agenda*, in Deakin, S. and Hughes, A. (Eds), *Enterprise and*

Community: New Directions in Corporate Governance, Blackwell Publishers, Oxford.

Deng, L., & Wang, J. (2006). Corporate governance and financial distress. Evidence from Chinese listed companies. *The Chinese Economy*, 39(5), 5–27.

Department of Statistics (2013). 2005 – 2013 National accounts small and medium enterprises. *Department of Statistics Malaysia*. Available at https://www.dosm.gov.my/v1/uploads/files/4_Portal%20Content/3_Methods%20%26%20Classification/1_Metadata/2_Metadata%20-%20Publication%20Level/National%20Account/5_%20Metadata%20National%20Accounts%20SME_22Dis16.pdf

Department of Statistics (2012). Economic census 2011 profile of small and medium enterprise. *Putrajaya, Malaysia: Department of Statistics Malaysia*. Available at https://www.dosm.gov.my/v1/index.php?r=column/cone&menu_id=T2pLUVNDNFh2UGw5azJvYzRJOWFMZz09

DOSM (2017). Economic Census 2016: Establishment Statistics. Available at https://www.dosm.gov.my/v1/index.php?r=column/cthemByCat&cat=431&bulid=KzRDejQ0d0tXenpsRFFXOEpKaDc4UT09&menu_id=WjJGK0Z5bTk1ZEIVT09yUW1tRG41Zz09

Derksen, S. & Keselman, H. (1992). Backward, forward and stepwise automated subset selection algorithms: Frequency of obtaining authentic and noise variables. *British Journal of Mathematical and Statistical Psychology*, 45, 265–282.

Dimitras A., Zanakis S. & Zopudinis C. (1996). A survey of business failures with an emphasis on failure prediction methods and industrial applications. *European Journal of Operational Research*, 90 (3), 487-513.

DiPietro, W., & Sawhney, B. (1977). Business Failures, Managerial Competence, and Macroeconomic Variables, *American Journal of Small Business*, II (2), 4–15.

Dirickx, Y. & Van Landeghem, G. (1994). Statistical failure previsions problems, *Tijdschrift voor Economie en Management*, Vol. XXXIX(4), 429 – 462.

- Donaldson, G. (1961). Corporate debt capacity: A study of corporate debt policy and the determination of corporate debt capacity, *Boston: Division of Research*, Harvard School of Business Administration.
- Donaldson, L., (1985). *In defence of organization theory, A reply to the critics*, Cambridge, Cambridge University Press.
- Donaldson, L., & Davis, J. (1991). Stewardship theory or agency theory: CEO governance and shareholder returns. *Australian Journal of Management*, 16(1), 49–64.
- Doumplos, M., & Zopoudinis, C., (1999). A multicriteria discrimination method for the prediction of financial distress: the case of Greece. *Multinational Finance Journal*, 3(2), 71-101.
- Douma, S., George, R., & Kabir, R. (2006). Foreign and domestic ownership, business groups, and firm performance: Evidence from a large emerging market, *Strategic Management Journal*, 27(7), 637-657.
- Dowell, G., Shackell, M., & Stuart, N. (2011). Boards, CEOs, and surviving a financial crisis: Evidence from the internet shakeout. *Strategic Management Journal*, 32(10), 1025–1045.
- Edmister, R. (1972). An empirical test of financial ratio analysis for small business failure prediction, *Journal of Financial and Quantitative Analysis*, 1477-1493.
- Eickelpasch, A., Hirte, G., & Stephan, A. (2015). Firm's evaluation of location quality: Evidence from East Germany. *German Institute for Economic Research, Discussion Paper*, 58, 1-38.
- Eisenbeis, (1977). Pitfalls in the application of discriminant analysis in business. *Journal of Finance*, 32(3), 875-900.
- Eisenberg, T., Sundgren, S., & Wells, M. (1998). Larger board size and decreasing firm value in small firms, *Journal of Financial Economics*, 48, 35-54.
- Eisenhardt, K. (1989). Agency theory: An assessment and review. *Academy of Management Review*, 57-74.

- Eniola, A. (2015). We can double Lagos GDP, says Ambode. The Punch NG.
Retrieved 16 March 2015. Available at <http://www.latestnigeriannews.com/news/1079836/we-can-double-lagos-gdp-says-ambode.html>
- Ericson, R., & Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies*, 62, 53-82.
- Elliot, J. & Kennedy, D. (1988). Estimation and prediction of categorical models in accounting research. *Journal of Accounting Literature*, 13(1), 202-42.
- Elloumi, F., & Gueyié, J. (2001). Financial distress and corporate governance: an empirical analysis, Corporate Governance. *The International Journal of Business in Society*, 1(1), 15 – 23.
- EU (2014). A recovery on the horizon? Annual report on European SMES 2012/2013.
- Everett, J. & Watson, J. (1998). Small business failure and external risk factors. *Small Business Economics*, 1998, 11(4), 371-90.
- Faccioa, M., Marchicab, M., & Mura, R. (2016). CEO gender, corporate risk-taking, and the efficiency of capital allocation. *Journal of Corporate Finance*, 39, 193–209.
- Fairlie, R.W., & Robb, M. (2009). Gender differences in business performance: Evidence from the characteristics of business owners survey. *Small Business Economics*, 33(4), 375–395
- Fama, E. (1980). Agency problems and the theory of the firm. *Journal of Political Economy*, 88(2), 288-307
- Fama, E., & Jensen, M. (1983). Separation of ownership and control. *The Journal of Law and Economics*, 26(2), 301-325.
- Fasci, M., & Valdez, J. (1998). A performance contrast of male- and female owned small accounting practices. *Journal of Small Business Management*, 36(3), 1–7.

- Fernandez, E., & Olmeda, I. (1995). Bankruptcy prediction with artificial neural networks. *International Workshop on Artificial Neural Networks, IWANN '95, Malaga-Torremolinos, Spain, June 7-9, 1995*.
- Fischer, E., Reuber, A., & Dyke, L. (1993). A theoretical overview and extension of research on sex, gender, and entrepreneurship. *Journal of Business Venturing*, 8, 151-168.
- FitzPatrick, P. (1932). A comparison of ratios of successful industrial enterprises with those of failed companies. *The Certified Public Accountant* (October, November, December): 598-605, 656-662, and 727-731, respectively.
- Flerackers, P. (1998). Het success van Nieuwe Bedrijven: Slaag- en Faalfactoren van Nieuwe Bedrijven in Nederland, Master thesis, Faculty of Social Sciences, Utrecht.
- Florackis, C. (2008). Agency costs and corporate governance mechanisms: evidence for UK firms, *International Journal of Managerial Finance*, 4(1), 37 - 59
- Ferreira, S., Grammatikos, T., & Michala, D. (2014). Forecasting distress in European SME portfolios. Available at SSRN: <http://ssrn.com/abstract=2266426> or <http://dx.doi.org/10.2139/ssrn.2266426>
- Fidrmuc, J., Hainz, C., & Malesich, A. (2006). Default rates in the loan market for SMEs: Evidence from Slovakia. *William Davidson Institute Working Paper*, Number 854.
- Fidrmuc, J. & Hainz, C. (2010). Default rates in the loan market for SMEs: Evidence from Slovakia. *Economic Systems*, 34(2), 479-496.
- Fitz, P. (1932). A Comparison of ratios of successful industrial enterprises with those of failed firms, *Certified Public Accountant*, 598-605.
- Fletcher, D. & Goss, E. (1993). Forecasting with neural network: an application using bankruptcy data, *Information and Management*, 24(3), 159-67.
- Fondas, N., & Salsalos, S. (2000). A different voice in the boardroom: How the presence of women directors affects board influence over management. *Global Focus*, 12(2), 13-22.

- Ford, R., & Richardson, W. (1994). Ethical decision making: A review of the empirical literature. *Journal of Business Ethics*, 13(3), 205–221.
- Frank, M. & Goyal, V. (2004). Capital structure decision: Which factors are reliably important? *Working Paper*, University of British Columbia.
- Fuller-Love, N., Midmore, P., & Thomas, D. (2006). Entrepreneurship and rural economic development: a scenario analysis approach. *International Journal of Entrepreneurial Behaviour & Research*, 12(5), 289-305.
- Garcia-Posada, M. & Mora-Sanguinetti, J. (2013). Are there alternatives to bankruptcy? A study of small business distress in Spain. *Banco de Espana Working Paper No. 1315*. Available at SSRN: <http://ssrn.com/abstract=2341527>
- Garson, G.D., (1991). Interpreting neural-network connection weights. *Artif. Intell. Expert*, 6, 47–51.
- Gbandi, E. & Amissah, G. (2014). Financing options for small and medium enterprises (SMEs) in Nigeria. *European Scientific Journal*, 10(1), 327 – 340.
- Gentry, A., Newbold, P., & Whitford, D. (1985). Classifying bankrupt firms with funds flow components. *Journal of Accounting Research*, 23(1), 146-160.
- Gepp, A., & Kumar, K. (2012). Business failure prediction using statistical techniques: A review. *Bond Business School Publications*. Paper 675.
- Goodstein, J., Gautam, K., & Boeker, W. (1994). The effects of board size and diversity on strategic change. *Strategic Management Journal*, 15(3), 241–250.
- Hambrick, D., & D'Aveni, R. (1992). Top team deterioration as part of the downward spiral of large corporate bankruptcies. *Management Science*, 38, 1445-1466.
- Gorodnichenko, Y., & Roland, G. (2011). Individualism, innovation, and long-run growth. *PNAS*, 108(4), 21316–21319.
- Gujarati, D.N. (2003). *Basic econometrics*. New York: McGraw Hill Book Co.
- Gunto, M., & Haji, M. (2013). SMEs development in Malaysia: Lesson for Libya, *Prosiding PERKEM*, 8(3), 1521-1530.

- Graen, G. & Scandura, T., (1987). Toward a psychology of dyadic organizing, In B. Slaw, and L.L. Cummings (Eds.). *Research in Organizational Behavior*, 9, 175-208.
- Gray, D., Saunders, M., & Goregaokar, H. (2012). Success in challenging times: Key lessons for UK SMEs, *Working Paper*, University of Surrey.
- Hair, J., Black, W., Babin, B., & Anderson, R (2010). *Multivariate Data Analysis*, 7/E, Prentice Hall, New York.
- Hall, G., & Young, B. (1991). Factors associated with insolvency amongst small firms. *International Small Business Journal*, 9(2), 54–63.
- Hambrick, D., Cho, T., & Chen, M. (1996). The influence of top management team heterogeneity on firms' competitive moves. *Administrative Science Quarterly*, 41, 659-684.
- Hambrick, D., & D'Aveni, R. (1992). Top team deterioration as part of the downward spiral of large corporate bankruptcies. *Management Science*, 38(10), 1445–1466.
- Hamer, M. (1983). Failure prediction: Sensitivity of classification accuracy to alternative statistical methods and variable sets. *Journal of Accounting and Public Policy*, 2(4), 287-307.
- Haniffa, R. & Cooke, T. (2000). Culture, corporate governance and disclosure in Malaysian corporations. *Asian AAA World Conference in Singapore*, 28-30 August 2000.
- Hart, O. (1995). Corporate governance: Some theory and implications. *The Economic Journal*, 105(430), 678-98.
- Haslam, S., & Ryan, M. (2008). The road to the glass cliff: Differences in the perceived suitability of men and women for leadership positions in succeeding and failing organizations. *The Leadership Quarterly*, 19, 530-546.
- Hay, D., Knechel, W., & Wong, N. (2006). Audit fees: A meta-analysis of the effect of supply and demand attributes. *Contemporary Accounting Research*, 23 (1), 141-191.

- Headd, B. (2003). Redefining business success: Distinguishing between closure and failure. *Small Business Economics*, 21, 51-61.
- Hermalin, E., & Weisbach, S. (2003). Boards of directors as an endogenously determined institution: A survey of the economic literature. *FRBNY Economic Policy Review*, 7 – 26.
- Hermalin, B., & Weisbach, M. (1988). The determinants of board composition. *Rand Journal of Economics*, 19(4), 589-606.
- Hillman, A., & Dalziel, T. (2003). Boards of directors and firm performance: Integrating agency and resource dependence perspectives. *Academy of Management Review*, 28(3), 383–396.
- Hirshleifer, J. (1966). Investment decisions under uncertainty: Application of the state-preference approach. *Quarterly Journal of Economics*, 80, 262-27.
- Hu, H. & Sathye, M. (2015). Predicting financial distress in the Hong Kong growth enterprises market from the perspective of financial sustainability. *Sustainability*, 7, 1186-1200.
- Hudson, J. (1989). The birth and death of firms. *Quarterly Review of Economics and Business*, 29(2), 68–86.
- Huse, M., & Solberg, A. (2006). Gender related boardroom dynamics: How Scandinavian women make and can make contributions on corporate boards. *Women in Management Review*, 21(2), 113-130.
- Hofstede, G. (1991). Management in a multicultural society. *Malaysian Management Review*, 26(1), 3-12.
- Houben, G. (2000). De Eigenheid van het Startproces Vertaald in een Aangepast Ondernemingsplan. Ph.D. dissertation. Limburgs Universitair Centrum
- Houben, G., Bakker, W., & Vergauwen, P. (2005). Assessing the non-financial predictors of the success and failure of young firms in the Netherlands. *Journal of Economics and Applied Informatics*, 1, 5-14.

- Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2, 359-366.
- Hosmer, W., & Lemeshow, S. (2000). *Applied Logistic Regression*, 2nd Ed. John Wiley & Sons, Inc.
- Hsu, C., Kuo, L., & Chang, B. (2013). Gender difference in profit performance—evidence from the owners of small public accounting practices. *Asian Journal of Finance & Accounting*, 5(1), 140–159.
- Inmyxai, S., & Takahashi, Y. (2010). Performance contrast and its determinants between male and female headed firms in Lao MSMEs. *International Journal of Business and Management*, 5(4), 37–52.
- Ishak, Z., & Napier, C. (2006). Expropriation of minority interests and corporate diversification in Malaysia. *Asian Academy of Management Journal of Accounting and Finance*, 2, 85–113.
- Isik, O., & Soykan, M. (2013). Large shareholders and firm performance: Evidence from Turkey. *European Scientific Journal*, 9(25), 23 – 37.
- Jabeur, B. (2014). Macroeconomic variables in financial distress: A non-parametric method, *IPAG Working Papers 2014*, 313, 1-12.
- Jahur, M., & Quadar, S. (2012). Financial distress in small and medium enterprises (SMEs) of Bangladesh: Determinants and remedial measures. *Economia Series Management*, 15(1), 432-444.
- Jamali, D., Safieddine, A., & Daouk, M. (2007). Corporate governance and women: An empirical study of top and middle women managers in Labanese banking sector. *Corporate Governance*, 7(5), 574-585.
- Jensen, M., & Meckling, W. (1976). Theory of the firm: Managerial behaviour, agency costs and ownership structure, *Journal of financial Economics*, 3, 305 – 360.
- Jensen, M. (1993). The modern industrial revolution, exit, and the failure of internal control systems, *Journal of Finance*, 48, 831-880.

- Joos, P., Vanhoof, K., Ooghe, H., & Sierens N. (1998). Credit classification: A comparison of logit models and decision trees. Proceedings Notes of the Workshop on Application of Machine Learning and Data Mining in Finance, *10th European Conference on Machine Learning*, April 24, Chemnitz (Germany), 59-72.
- Joos, P, Ooghe, H., & Sierens, N. (1998). Methodologie bij het opstellen en beoordelen van kredietclassificatiemodellen. *Tijdschrift voor Economie en Management*, 18(1), 1-48.
- Jovanovic, B. (1982). Selection and the evolution of Industry, *Econometrica*, 50, 649–670.
- Joy, O., & Tollefson, J. (1975). On the financial applications of discriminant analysis. *Journal of Financial and Quantitative Analysis*, 10(5), 723-739.
- Judge, W., & Zeithaml, C. (1992). Institutional and strategic choice perspectives on board involvement in the strategic decision process. *Academy of Management Journal*, 35(4), 766–794.
- Kadiri, I. (2012). Small and medium scale enterprises and employment generation in Nigeria: The role of finance. *Kuwait Chapter of Arabian Journal of Business and Management Review*, 1(9), 66–79
- Kam A, Citron, D. & Muradoglu, G. (2008). Distress and restructuring in China: Does ownership matter? *China Economic Review*, 19(4), 567-579.
- Karels G., & Prakash, A. (1987) Multivariate normality and forecasting of bankruptcy. *Journal of Business Finance & Accounting*, 14(4), 573-593.
- Karim, A. & Suhaimi, A. (2013). Factors affecting small and medium enterprises success: An exploratory study. *Jurnal Teknologi (Social Sciences,)* 64(3), 69–72.
- Keasey, K., & Watson R. (1987). Non-financial symptoms and the prediction of small company failure: a test of Argenti's hypotheses, *Journal of Business Finance and Accounting*, 14(3), 335-354.

- Keasey, K., Thompson, S., & Wright, M. (1997). Introduction: the corporate governance problem: Competing diagnoses and solutions, in Keasey, K., Thompson, S. and Wright, M. (Eds), *Corporate Governance: Economic and Financial Issues*, Oxford University Press, Oxford, 1-17.
- Kerling, M., & Poddig, T. (1994). *Klassifikation von Unternehmen mittels KNN*. In: Rehkgugler, H. – Zimmermann, H. G. (eds): *Neuronale Netze in der Ökonomie*. München: Vahlen Verlag: 424–490.
- Keynes, J. M. (2008). *The General Theory of Employment, Interest and Money*. Chapter 19: BN Publishing.
- Khan, W., & Vieito, J. (2013). CEO gender and firm performance. *Journal of Economics and Business*, 67, 55–66.
- Kim, K., Al-Shammari, H., Kim, B., & Lee, S. (2009). CEO duality leadership and corporate diversification behavior. *Journal of Business Research*, 62(11), 1173–1180.
- Kim-Soon, N., Mohammed, A. & Agob, F. (2013). A Study of financial distress companies listed in the Malaysian Stock Exchange using financial liquidity ratios and Altman's model. *European Journal of Scientific Research*, 114(4), 513-525.
- King, M. (1977). *Public policy and the corporation*. Chapman and Hall Publishers, London, 87-91.
- Khorasgani, A. (2011). The optimal model for UK SMEs credit risk considering the industry and corporate governance effects. *International Conference on Business and Management* April 2011, Izmir, Turkey.
- Klapper, F. & Love, I. (2004). Corporate governance, investor protection, and performance in emerging markets, *Journal of Corporate Finance*, 10 (5), 703–728.
- Kumar, K., & Thakur, G. (2012). Extracting explanation from artificial neural network. *International Journal of Computer Science and Information Technologies*. Vol 3 (2), 3812-3815.

- Kumar, K., & Bhattacharya, S. (2006). Artificial neural network vs linear discriminant analysis in credit ratings forecast, *Review of Accounting and Finance*, 5 (3), 216 – 227.
- Kraus, A., & Litzenberger, H. (1973). A state-preference model of optimal financial leverage. *The Journal of Finance*, 28(4), 911-922.
- Lau, A. (1987). A five-state financial distress prediction model. *Journal of Accounting Research*, 25(1), 127-138.
- La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (1999). Corporate ownership around the world. *Journal of Finance*, 54, 471–517.
- Laitinen, T., & Kankaanpää, M. (1999). Comparative analysis of failure prediction methods: the Finnish case. *The European Accounting Review*, 8(1), 67-92.
- Larcker, D. F. and Rusticus, T. O. (2005). On the use of instrumental variables in accounting research, *Working Paper*, University of Pennsylvania. Available at: <http://ssrn.com/abstract=694824>.
- Lee, P., & O'Neill, H. (2003). Ownership structures and R&D investments of US and Japanese firms: Agency and stewardship perspectives. *Academy of Management Journal*, 46(2), 212-225.
- Lee K., Booth, D., & Alam, P. (2005). A comparison of supervised and unsupervised neural networks in predicting bankruptcy of Korean firms. *Expert Systems with Applications*, 29, 1-16.
- Lennox, C. (1999). Identifying failing companies: A re-evaluation of the logit, probit, and DA approaches. *Journal of Economics and Business*, 51(4), 347-364.
- Lehmann B., (2003). Is it worth the while? The relevance of qualitative information in credit rating. *Working Paper presented at the EFMA 2003 Meetings*, Helsinki, 1-25.
- Lehn, K., Sukesh, P. & Zhao, M. (2004). Determinants of the size and structure of corporate boards: 1935-2000, *Working Paper*, Katz Graduate School of Business.

- Letendre, L. (2004). The dynamics of the boardroom. *Academy of Management Executive*, 18(1), 101–104.
- Leung, D., & Rispoli, L. (2011). The contribution of small and medium-sized businesses to gross domestic product: A Canada–United States comparison, *Economic Analysis (EA) Research Paper Series*, 11F0027M — No. 070, ISSN 1703-0404.
- Lichtenstein, B., & Brush, C. (2001). How do “resource bundles” develop and change in new ventures? A dynamic model and longitudinal exploration Entrepreneurship. *Theory and Practice*, 25, 37-58
- Liu, J., (2004). Macroeconomic determinants of business failures in the UK. *Applied Economics*, 36(4), 939-935.
- Liu, J. (2009). Business failures and macroeconomic factors in the UK. *Bulletin of Economic Research*, 61(1), 47–72.
- Lipton, M. & Lorsch, J. W. (1992). A modest proposal for improved corporate governance, *Business Lawyer*, 48(1), 59-77.
- Liu, J. & Pang, D. (2009). Financial factors and company investment decisions in transitional China. *Managerial and Decisions Economics*, 30(2), 91-108.
- Liu, J. and Wilson, N. (2002). Corporate failures and the impact of the 1986 Insolvency Act. *Managerial Finance*, 28(6), 61-71.
- Loscocco, K. A., Robinson, J., Hall, R. H., & Allen, J. K. (1991). Gender and small business success: An inquiry into women’s relative disadvantage. *Social Forces*, 70(1), 65-85.
- Lugovskaja, L. (2009). Predicting default of Russian SMEs on the basis of financial and non-financial variables. *Journal of Financial Services Marketing*, 14(4), 301-313.
- Luppi, B., Marzo, M. & Scorcu, E. (2007). A credit risk model for Italian SMEs, *Working papers / Università di Bologna, Dipartimento Scienze Economiche*, 600.

- Lussier, R. (1995). A non-financial business success versus failure prediction model for young firms. *Journal of Small Business Management*, 33(1), 8-20.
- Lussier, R., & Pfeifer, S. (2000). Business success and failure comparisons between the US and East Central Europe Croatia. *Entrepreneurship Theory and Practice*, 24(4), 59-67.
- Lussier, R., & Halabi, E. (2010). A three-country comparison of the business success versus failure prediction model. *Journal of Small Business Management*, 48(3), 360–377.
- Mackinnon, M.J. and Glick, N. (1999). Data mining and knowledge discovery in databases - an overview. *Australian and New Zealand Journal of Statistics*, 41(3), 255-276.
- Mačerinskienė, I., & Mendelsonas, T. (2013). Macroeconomic determinants of corporate insolvency. *KSI Transactions on Knowledge Society*, 6(3), 35-40
- Majumdar, K. (1997). The impact of size and age on firm-level performance: Some evidence from India. *Review of Industrial Organization*, 12, 231–241
- Mallette, P., & Fowler, K. (1992). Effects of board composition and stock ownership on the adoption of poison pills. *Academy of Management Journal*, 35(5), 1010–1035.
- Mannasoo, K., & Mayes, D. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking and Finance*, 33(2), 244-253.
- Markwell, Donald (2006). *John Maynard Keynes and International Relations: Economic Paths to War and Peace*. New York: Oxford University Press.
- Marouani, A. & Bellier, A. (2014). Detecting early indicators of SMEs failure: survival analysis techniques. Available at SSRN: <http://ssrn.com/abstract=2505915>
- Mayer, F. (1997). *Corporate governance, competition, and performance*, in Deakin, S. and Hughes, A. (Eds), *Enterprise and Community: New Directions in Corporate Governance*, Blackwell Publishers, Oxford.

- Mazzarol, T. (2013). Small business policy for 2013: What should be on the list. *The Conversation*, retrieved 2 June, 2015 from, <http://theconversation.com/small-business-policy-for-2013-what-should-be-on-the-list-11902>
- Mcleay, S., & Omar, A. (2000). The sensitivity of prediction models to the non-normality of bounded and unbounded financial ratios. *British Accounting Review*, 32, 213-230.
- McNally, J. & Tophoff, H. (2014). Leveraging effective risk management and internal control. *International Federation of Accountants (IFAC)*, 21-36.
- Md-Rus, R., Nisham K., Abdul Latif, R., & Nadakkavil, Z. (2013). Ownership structure and financial distressed. *Journal of Advanced Management Science*, 1(4), 363-267.
- Memić, D. (2015). Assessing credit default using logistic regression and multiple discriminant analysis: Empirical evidence from Bosnia and Herzegovina. *Interdisciplinary Description of Complex Systems*, 13(1), 128-153.
- Mensah, Y. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: A methodological study. *Journal of Accounting Research*, 22(1), 380-395.
- Meyer, D., Balemi, A., & Wearing, C. (2000). Neural nets - their use and abuse for small data sets. *Res.Lett.Math.Sci*, 1, 145–158.
- Michael J., & William C. (2013). Small business borrowing and the bifurcated economy: Why quantitative easing has been ineffective for small business. *Business Economics*, 48, 214-223.
- Miglani, S., Ahmed, K., & Henry, D. (2015). Voluntary corporate governance structure and financial distress: Evidence from Australia. *Journal of Contemporary Accounting & Economics*, 11, 18–30.
- Miguel, E., Shanker, S., & Ernest, S. (2004). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy*, 112(4), 725–753

- Milliken, F., & Martins, L. (1996). Searching for common threads: Understanding the multiple effects of diversity in organizational groups. *Academy of Management Review*, 21(2), 402.
- Millington, K. (1994). The impact of selected economic variables on new business formation and business failures. *The Journal of Small Business Finance*, 3(2), 177–179.
- Minai, M., & Lucky, E. (2011). The moderating effect of location on small firm performance: Empirical evidence. *International Journal of Business and Management*, 6(10), 178-192.
- Mine, U., & Hakan, A. (2006). Prediction of corporate financial distress in an emerging market: The case of Turkey. *Cross Cultural Management: An International Journal*, 13(4), 277 – 295.
- Mirchandani, K. (1998). Protecting the boundary: Teleworker insights on the expansive concept of "work." *Gender & Society*, 12(2), 168-87.
- Modigliani, F., & Miller, M. (1958). The cost of capital, corporate finance and the theory of investment. *American Economic Review*, 48, 261 – 297.
- Modigliani, F. & Miller, M. (1963). Corporate income taxes and the cost of capital: A correction. *The American Economic Review*, 53(3), 433-443.
- Mohd Noor, Z. & Mohd Iskandar, T. (2012). Corporate governance and corporate failure: A survival analysis. *Prosiding Perkem*, 7(1), 684 – 695.
- Monelos, P., & Rodríguez (2011). DEA as a business failure prediction tool Application to the case of galician SMEs. *Contaduría y Administración*, 59(2), 65-96.
- Moscalu, M. (2012). Business failure prediction for Romanian SMEs using multivariate discriminant analysis. *Revista Economica, Journal of economic-financial theory and practice*, 4, 457-466.
- Mossman, E., Bell, G., Swartz, L., & Turtle, H. (1998). An empirical comparison of bankruptcy models. *The Financial Review*, 33(2), 35-54.

- Mueller, G., & Barker, V. (1997). Upper echelons and board characteristics of turnaround and non-turnaround declining firms. *Journal of Business Research*, 39, 119-134.
- Muhammad, S., & Bala, G. (2013). An assessment of the contribution of commercial banks to the growth of small and medium scale enterprises in Nigeria, *International Journal of Research In Social Sciences*, 2(4), 47 – 55.
- Murtaza, M., & Shah, J. (2000). A neural network based clustering procedure for bankruptcy prediction. *American Business Review*, 18(2), 80-86.
- Myers, S. (1984). The capital structure puzzle, *Journal of Finance*, 39, 575 – 592.
- NBS (2010). Survey report on micro, small and medium enterprises (MSMEs) in Nigeria, National Bureau of Statistics, Nigeria. Available at https://nigerianstat.gov.ng/pdfuploads/SMEDAN%202013_Selected%20Tables.pdf
- Neophytou E, Charitou A, & Charalambous C. (2001). Predicting corporate failure: empirical evidence for the UK. *Working Paper, University of Southampton, Department of Accounting and Management Science*, 1-29.
- Norfian, M. (2013). Prediction of financial distress companies in Malaysia: a comparison between consumer products and industrial products sectors, *2nd International Conference on Management, Economics and Finance (2nd ICMEF 2013) Proceeding*, ISBN: 978-967-5705-12-0, 382-392.
- NSDC (2013). Guidelines for New SME Definition, SME Corp. Malaysia, retrieved from <http://www.smecorp.gov.my/vn2/node/533>
- Odom, M. & Sharda, R. (1990). A neural network model for bankruptcy prediction, *Proceedings of the IEEE International Conference on Neural Networks*, San Diego, CA, 1163-8.
- Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18, 109-131.
- Ooghe, H., Joos P., & De Bourdeaudhuij C. (1995). Financial distressed models in Belgium: The results of a decade of empirical research. *International Journal of Accounting*, 30, 245-274.

- Ooghe, H., Joos, P., & De Vos, D. (1993). Risico-indicator voor een onderneming aan de hand van falingspredictie-modellen. *Accountancy en Bedrijfskunde Kwartaalschrift*, 18(3), 3-26.
- Ooghe, H., Joos, P., De Vos, D., & De Bourdeaudhuij, C. (1994). Towards an improved method of evaluation of financial distress models and presentation of their results. *Working Paper, January 1994, Department of Corporate Finance*, Ghent University, Belgium, 22.
- Ortecho, L., & Bengoa, A. (2014). Enhancing the competitiveness of SMEs through the innovative cooperative business model (CBM). *APEC Small and Medium Enterprises*, retrieved from <http://publications.apec.org/publication-detail.php?pubid=1520>
- Oseifuah, K. & Gyekye, B. (2013). Internal control in small and microenterprises in the Vhembe district, Limpopo province, South Africa. *European Scientific Journal*, 9(4), 241-251.
- O'Sullivan, Arthur; Sheffrin, Steven M. (2003). *Economics: Principles in Action*. Upper Saddle River: Pearson Prentice Hall.
- Ozesmi, S. & Ozesmi, U. (1999). An artificial neural network approach to spatial habitat modelling with interspecific interaction. *Ecol. Model.* 116, 15–31.
- Palat, P. (1989). *Understanding ratios – A practice guide for business, finance and banking*, Kogan Page Ltd., London.
- Pandey, M. (2004). Capital structure, profitability and market structure: evidence from Malaysia. *Asia Pacific Journal of Economics and Business*, 8(2), 45.
- Parker, G., Peters, F., & Turetsky, H. (2002). Corporate governance and corporate failure: A survival analysis. *Corporate Governance*, 2, 4-12.
- Park, S. (2005). A comparative study of logit and artificial neural networks in predicting bankruptcy in the hospitality industry. Unpublished Masters Thesis, Oklahoma State University.

- Partington, G., Russell, P., Stevenson M., & Torbey, V. (2001). Predicting return outcomes for the shareholders of companies entering chapter 11 bankruptcy. *Managerial Finance*, 27(5), 143-168.
- Patuwo, E., Hu, Y., & Hung, S. (1993). Two-group classification using neural networks. *Decision Sciences*, 24(4), 825–845
- Pederzoli, C. & Torricelli, C. (2010). A parsimonious default prediction model for Italian SMEs, *Banks and Bank Systems*, 5(4), 5-9.
- Peni, E. (2014). CEO and chairperson characteristics and firm performance. *Journal of Management and Governance*, 18(1), 185–205.
- Penrose, E. (1959). *The theory of the growth of the firm*. New York, John Wiley
- Pervan, I., & Kuvek, T. (2013). The relative importance of financial ratios and nonfinancial variables in predicting of insolvency. *Croatian Operational Research Review*, 13(4), 187-197.
- Peterson, R., Kozmetsky, G., & Ridgway, N. (1983). Perceived causes of small business failures: A research note. *American Journal of Small Business*, VIII (1), 15–19.
- Pfeffer, J., & Salancik, G. (1978). *The external control of organizations: A resource dependence perspective*. New York, Harper & Row.
- Phelps, N., Fallon, R. & Williams, C. (2001). Small firms, borrowed size and the urban-rural shift. *Regional Studies*, 35(7), 613-624.
- Pindado J, & Rodrigues L. (2005). Determinants of financial distress costs. *Financial Markets and Portfolio Management*, 19(4), 343–359.
- Platt, H., & Platt, M. (1990). A note on the use of industry-relative ratios in bankruptcy prediction. *Journal of Banking and Finance*, 15(6), 1183-1194.
- Plattner, D. (2002). Why firms go bankrupt. The influence of key financial figures and other factors on the insolvency probability of small and medium sized enterprises. *KfW Research*, 28, 37–51.

- Pofeldt, E. (2016). Cities leading the way in loans to American entrepreneurs. CNBC. Available at <https://www.cnn.com/2016/08/18/these-25-cities-are-best-for-small-business-loan-approvals.html>
- Pregibon, D. (1980). Goodness of link tests for generalized linear models. *Appl. Statist.*, 29, 15-24.
- Press, J., & Wilson, S. (1978). Choosing between logistic regression and discriminant analysis. *Journal of the American Statistical Association*, 73(364), 699-705
- PwC, (2013). 2013 Ghana banking survey harnessing the SME potential, PricewaterhouseCoopers, 2013. Available at <https://www.pwc.com/gh/en/assets/pdf/2016-banking-survey-report.pdf>
- Raheja, C. (2005). Determinants of board size and composition: A theory of corporate boards. *Journal of Financial and Quantitative Analysis*, 40, 283–306.
- Rajan, G. & Zingales, L. (1995). Do we know about capital structure? Some evidence from international data. *The Journal of Finance*, 50, 1421-60.
- Reynolds, P. (1987). New firms: Societal contribution versus survival potential. *Journal of Business Venturing*, 2(3), 231-246.
- Richardson, F., & Davidson L. (1984). On linear discrimination with accounting ratios. *Journal of Business Finance and Accounting*, 11(4), 511-525.
- Roberson, M. & Park, H. (2007). Examining the link between diversity and firm performance: The effects of diversity reputation and leader racial diversity. *Group & Organization Management*, 32, 548-568.
- Robb, A. (2008). An investigation of new firm performance by owner race, ethnicity, and gender. Available at <http://sbaer.uca.edu/research/sbi/2008/chalo3f.html>
- Robb, A., & Watson, J. (2010). Comparing the performance of female- and male controlled SMEs: Evidence from the United States and Australia. *Frontiers of Entrepreneurship Research*, 30(8), 1–12.

- Robichek, A. & Myers, S. (1965). *Optimal Financing Decisions*, Englewood Cliffs, N.J., PrenticeHall.
- Roe, M. (2004). The Institutions of Corporate Governance. *Harvard Law School John M. Olin Center for Law, Economics and Business Discussion Paper Series*, 488, 1-28.
- Rommer, D. (2005). A comparative analysis of the determinants of financial distress in French, Italian and Spanish firms. *Danmarks National Bank Working Papers* 2005, 26, 1-80.
- Roulston, M. S. (2007). Performance targets and the Brier score. *Meteorological Applications*, 14(2), 185-194.
- Ryan, K., Haslam, S., & Postmes, T. (2007). Reactions to the glass cliff: Gender differences in the explanations for the precariousness of women's leadership positions. *Journal of Organizational Change Management*, 20(2), 182-197,
- Ryan, K., Haslam, S., Hersby, D., & Bongiorno, R. (2011). Think crisis-think female: the glass cliff and contextual variation in the think manager-think male stereotype. *Journal of Applied Psychology*, 96(3), 470–84.
- Sajter, D. (2008). Economic aspects of bankruptcy and restructuring in bankruptcy, Doctoral dissertation, Faculty of Economics, University of J. J. Strossmayer in Osijek.
- Salchenberger, M., Cinar, E., & Lash, A. (1992). Neural networks: A new tool for predicting thrift failures. *Decision Sciences*, 23(4), 899–916.
- Salman, A., Fuchs, M., & Zampatti, D. (2015). Assessing risk factors of business failure in the manufacturing sector: A count data approach from Sweden. *International Journal of Economics, Commerce and Management*, 3(9), 42-62.
- Šarlija, N. (2002). Credit risk models in assessing the creditworthiness of small businesses. Ph.D. Thesis. In Croatian. University of Zagreb, Zagreb.
- Sarlija, N., & Jeger, M. (2011). Comparing financial distress prediction models before and during recession. *Croatian Operational Research Review (CRORR)*, 2, 133-142.

- Schultz, E., Tan, D., & Walsh, D., (2015). Corporate governance and the probability of default. *Accounting and Finance*, 57 (Suppl.), 235–253
- Schwartz, E., & van Tassel, R. (1950). Some suggested changes in the corporate tax structure. *The Journal of Finance*, 5(4), 410-20.
- Securities Commission Malaysia, (2017). Malaysian code on corporate governance (MCCG, 2017). *Securities Commission Malaysia*, Online. Retrieved 30 October, 2017 from <https://www.sc.com.my/wp-content/uploads/eng/html/cg/mccg2017.pdf>
- Service (2016). States & Regions. Available at <http://services.gov.ng/states>
- Shane, S. (1996). Hybrid organizational arrangements and their implications for company growth and survival: A study of new franchisors. *Academy of Management Journal*, 39(1), 216–234.
- Shin, K., & Lee, Y. (2002). A genetic algorithm application in bankruptcy prediction modelling. *Experts Systems with Applications*, 23(3), 321-328.
- Shleifer, A., & Vishny, R. (1997). A survey of corporate governance. *Journal of Finance*, 52, 737–783.
- Shoorvarzy, R., Tuzandehjani, M., & Garkaz, M. (2012). The effect mitigating creditors-shareholder conflicts over dividend policy accounting conservatism: evidence from Iran. *World Applied Sciences Journal*, 17(2), 211-217.
- Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, 74 (1), 101-124.
- Simona, S. (2008). Estimating the negative impact of business failure on Lithuania, *Social Research*, 4 (14), 113 – 120.
- Singhathep, T. & Pholphirul, P. (2015). Female CEOs, Firm Performance, and Firm Development: Evidence from Thai Manufacturers. *Gender, Technology and Development*, 19(3) 320–345.
- Siow, H., Singh, G. & Anwar, S. (2011). A success versus failure prediction model for small businesses in Singapore. *American Journal of Business*, 26(1), 50 – 64.

- Sirirattanaphonkun, S., & Pattarathammas, M. (2012). Default prediction for small-medium enterprises in emerging market: Evidence from Thailand. *Seoul Journal of Business*, 18(2), 25-54.
- SME Corp. (2017). Budget 2017 comment SME Corp Malaysia. Online. Retrieved 30 October, 2017 from <http://www.smecorp.gov.my/index.php/en/resources/2015-12-21-10-55-22/news/1793-budget-2017-comment-sme-corp-malaysia>
- SMECorps, (2013), Annual Report 2012/2013, SMECorp Malaysia.
- SMECorps, (2014), Annual Report 2013/2014, SMECorp Malaysia.
- SMEDAN (2003) National Policy on Micro, Small and Medium Scale Enterprises. Retrieved 2 June, 2015 from <http://www.smedan.gov.ng/search.Php?searwords/National%20policy%20on%20%msmes>
- Soderbom, M. (2009). Applied Econometrics. Lecture 2: Instrumental Variables, 2SLS and GMM. Available http://www.soderbom.net/lec2n_final.pdf
- Steele, A., (1995). Going concern qualifications and bankruptcy prediction. *European Accounting Association*, February 1995, 1-28.
- Stinchcombe, A. (1965). *Social structure and organizations*, in March, J. (Ed), Handbook of Organizations, Rand McNally, Chicago, IL, 142-193.
- Stiglitz, J. E. (2000). Capital market liberalization, economic growth, and instability. *World Development*, 28(6), 1075-1086.
- Stiglitz, J., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 74, 194-199
- Stinchcombe, A. (1965). *Social structure and organizations*. In March, J. G., editor, Handbook of Organizations, pages 142-193. Rand McNally, Chicago.
- Stock, J., & Yogo, M. (2005). Testing for weak instruments in linear IV regression, in identification and inference for econometric models: Essays in Honor of Thomas Rothenberg, Chap. 5, 80–108.

- Su, Y., Xu, D., & Phan, H. (2008). Principal–Principal Conflict in the Governance of the Chinese Public Corporation. *Management and Organization Review*, 4(1), 17–38.
- Sulaiman, M. (2001). Predicting corporate failure in Malaysia: An application of logit model to financial ratios. *Asian Academy of Management Journals*, 6(1), 99-118.
- Sullivan, T., Warren, E., & Westbrook, J. (1998). Financial difficulties of small businesses and reasons for their failure, *University of Texas at Austin*.
- Storey, D., Keasey, K., Watson, R., & Wynarczyk, P. (1987). *Performance of small firms: Profits, jobs and failure*. London: Croom Helm.
- Taffler, R. (1982). Forecasting company failure in the UK using discriminant analysis and financial ratio data. *Journal of the Royal Statistical Society*, 145(3), 342-358.
- Taffler, R. & Tisshaw, H. (1977). Going, going, gone - Four factors which predict. *Accountancy*, 88, 50-54.
- Tam, K., & Kiang, Y. (1992). Management applications of neural networks: The case of bank failure predictions. *Management Sci.*, 38(7), 926-947.
- Tam, K. (1991). Neural network models and the prediction of bank bankruptcy. *Omega: The International Journal of Management Science*, 19(5), 429 – 445.
- Tanthonongsakkun, S., Pitt, D., & Treepongkaruna, S. (2007). A comparison of corporate bankruptcy models in Australia: The Merton vs accounting-based models. *Working Paper*, ANU School of Finance and Applied Statistics.
- Teti, E., Dell’Acqua A., & Brambilla, M. (2012). Bankruptcy predictors during the financial crisis. A study of Italian SME’s, *World Finance Conference 2012*.
- Theodossiou, P. (1991). Alternative models for assessing the financial condition of business in Greece. *Journal of Business and Accounting*, 18(5), 697-720.
- Thornhill, S., & Amit, R. (2003). Learning about failure: Bankruptcy, firm age, and the resource-based view. *Organization Science*, 14(5), 497-509.

- Titman, S. & Wessels, R. (1988). The determinants of capital structure, *Journal of Finance*, 43, 1-19.
- Tucker, J. (1996). Neural networks versus logistic regression in financial modelling: a methodological comparison. *Paper published in Proceedings of the 1996 World First Online Workshop on Soft Computing (WSC1)*, Nagoya University, Japan, 19-30.
- Triandis, H. (1993). Collectivism and individualism a cultural syndromes. *Cross Cultural Research*, 27, 150-180.
- Tzeng, F. (2005). Opening the black box — Data driven visualization of neural networks. *IEEE Visualization*, (x), 383–390.
- Vallejo, M. (2009). The effects of commitment of non-family employees of family firms from the perspective of stewardship theory. *Journal of business ethics*, 87(3), 379-390.
- Vandergrift, D., & Brown, P. (2005). Gender differences in the use of high-variance strategies in tournament competition. *Journal of Socio-Economics*, 34(6), 834–849.
- Villalonga, B. & Amit, R. (2006). How do family ownership, control and management affect firm value? *Journal of Financial Economics*, 80(2), 385-417.
- Vlieghe, W. (2001). Indicators of fragility in the UK corporate sector. *Bank of England Working Paper No. 146*. Retrieved from SSRN: <http://ssrn.com/abstract=293186>
- Wadhwani, S. (1986). Inflation, bankruptcy, default premia and the stock market. *The Economic Journal*, 96, 120–138.
- Watson, J. (2002). Comparing the performance of male- and female-controlled businesses: Relating outputs to inputs. *Entrepreneurship Theory and Practice*, 26(3), 91–100.
- Watson, W., Kumar, K. & Michaelson, L. (1993). Cultural diversity's impact on interaction and performance: Comparing homogeneous and diverse task groups. *Academy of Management Journal*, 36(3), 590-602.

- Wei, X. (2007). Wage compensation for job-related illness: Evidence from a matched employer and employee survey in the UK. *Journal of Risk and Uncertainty*, 34(1), 85–99
- Weisbach, M. (1988). Outside directors and CEO turnover. *Journal of Financial Economics*, 20(1,2), 431–460.
- Westhead, P., Ucbasaran, D., Binks, M., (2004). Internationalization strategies selected by established rural and urban SMEs. *Journal of Small Business and Enterprise Development*, 11(1), 8-22.
- Whited, T. (1992). Debt, liquidity constraints and corporate investment evidence from panel data. *Journal of Finance*, 47, 1425-60.
- Wilson, R. L. & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, 11, 545-557.
- Wiklund, J., Baker, T., & Shepherd, D. (2010). The age-effect of financial indicators as buffers against the liability of newness. *Journal of Business Venturing*, 25, 423–437.
- Wiwattanakantang, Y. (2001). Controlling Shareholders and Corporate Value: Evidence from Thailand. *Pacific-Basin Finance Journal*, 9(4), 323–362.
- Williamson, O. (1985). *The economic institutions of capitalism: Firms, markets, relational contracting*. New York, Free Press.
- World Bank. (2016). Small is the new big – Malaysian SMEs help energize, drive economy. Available at <http://www.worldbank.org/en/news/feature/2016/07/05/small-is-the-new-big---malaysian-smes-help-energize-drive-economy>
- Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*, Cambridge, MA, MIT Press
- Xie, B., Davidson, W., & DaDalt, P. (2003). Earnings management and corporate governance: the role of the board and the audit committee. *Journal of Corporate Finance*, 9(3), 295-316.
- Yegnanarayana, B. (1999). *Artificial neural networks*. New Delhi, Prentice-Hall

- Yermack, D. (1996). Higher market valuation of companies with a small board of directors. *Journal of Financial Economics*, 40(2), 185-212.
- Young, G. (1995). Company liquidations, interest rates and debt. *Manchester School of Economic and Social Studies*, 63(0), 57-69.
- Zahra, S. A., Hayton, J. C., Neubaum, D. O., Dibrell, C., & Craig, J. (2008). Culture of family commitment and strategic flexibility: The moderating effect of stewardship. *Entrepreneurship Theory and Practice*, 32(6), 1035-1054.
- Zavgren C. (1983). The prediction of corporate failure: The state of the art, *Journal of Accounting Literature*, 2, 1-38.
- Zavgren, C. (1985). Assessing the vulnerability to failure of American industrial firms: A logistic analysis. *Journal of Business Finance and Accounting*, 12(1), 19-45.
- Zeitun, R. & Tian, G. (2007). Capital structure and corporate performance: Evidence from Jordan. *Australasian Accounting, Business and Finance Journal*, 1(4), 40-61.
- Zhang, J., Chung, T., & Oldenburg, K. (1999). A simple statistical parameter for use in evaluation and validation of high throughput screening assays. *Journal of Biomol Screen*, 4(2), 67-73.
- Zmijewski, M. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 22, 59-86.
- Zoppa, A., & McMahon, G. (2002). Pecking order theory and the financial structure of manufacturing SMEs from Australia's business longitudinal survey. *Small Enterprise Research*, 10(2), 23-41.
- Zulkarnian, M., Ali, M., Md. Nasir, A., & Mohamad, Z. (2001). Forecasting corporate failure in Malaysian industrial sector firms. *Asian Academy of Management Journals*, 6(1), 15-30.
- Zulkarnian, M. (2006). Prediction of corporate financial distress: evidence from Malaysian listed firms during the Asian financial crisis. *Staff Paper 2/2006*, University Putra Malaysia.

APPENDICES

APPENDIX 1: Logistic Regression for Malaysian Sample

APPENDIX 1a: Model 1 (3-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	550.442 ^a	.429	.572

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	2.901	8	.940

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	269	64	80.8
	Failed	65	268	80.5
	Overall Percentage			80.6

a. The cut value is .500

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	242	91	72.7
	Failed	43	290	87.1
	Overall Percentage			79.9

a. The cut value is .400

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a	EBIT	.361	1.352	1	.245	1.435
	ROE	-1.063	10.991	1	.001	.345
	TLA	1.591	43.031	1	.000	4.907

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.691	8	.464

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	236	91	72.2
	STATUS Failed	91	238	72.3
	Overall Percentage			72.3

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	
Step 1 ^a	GENDER	1.155	.207	31.172	1	.000	3.175
	MDD	.966	.231	17.435	1	.000	2.627
	NDIR	-.609	.113	28.952	1	.000	.544
	IND	.401	.257	2.424	1	.119	1.493
	CONT	.843	.197	18.349	1	.000	2.324
	CINA	.407	.266	2.336	1	.126	1.503
	INDIAN	1.263	.409	9.551	1	.002	3.538
	MELAYU	.855	.313	7.471	1	.006	2.352
	CPI	-.079	.121	.428	1	.513	.924
	GDP	.041	.035	1.335	1	.248	1.041
	BLR	2.206	1.897	1.352	1	.245	9.075
	EMPY	2.615	1.378	3.600	1	.058	13.662
	Constant	-.398	.454	.766	1	.381	.672

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY.

linktest

Iteration 0: log likelihood = -455.39694
Iteration 1: log likelihood = -366.61158
Iteration 2: log likelihood = -365.66665
Iteration 3: log likelihood = -365.66383
Iteration 4: log likelihood = -365.66383

Logistic regression

Number of obs = 657
LR chi2(2) = 179.47
Prob > chi2 = 0.0000
Pseudo R2 = 0.1970

Log likelihood = -365.66383

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.9988134	.0888126	11.25	0.000	.8247438 1.172883
_hatsq	-.0066124	.0695887	-0.10	0.924	-.1430038 .129779
_cons	.0070042	.1163959	0.06	0.952	-.2211275 .2351359

brier status var28

Mean probability of outcome 0.5015
of forecast 0.5015

Correlation 0.4945
ROC area 0.7834 p = 0.0000

Brier score 0.1889
Spiegelhalter's z-statistic -0.2701 p = 0.6065
Sanders-modified Brier score 0.1888
Sanders resolution 0.1869
Outcome index variance 0.2500
Murphy resolution 0.0631
Reliability-in-the-small 0.0019
Forecast variance 0.0592
Excess forecast variance 0.0447
Minimum forecast variance 0.0145
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.1203

APPENDIX 1c: Model 3 (3-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	467.129 ^a	.490	.654

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.493	8	.254

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage
		Non-Failed	Failed	Correct
Step 1	STATUS Non-Failed	276	51	84.4
	STATUS Failed	52	277	84.2
	Overall Percentage			84.3

a. The cut value is .500

Model	Estimates	Plot	Statistics	Code	Log	Output	Notes
Fit Statistic	Label	Training	Validation	Test			
AIC	Akaike's Information Criterion	438.32103811					.
ASE	Average Squared Error	0.1082335505	0.1249985712				.
AVERR	Average Error Function	0.3473930939	0.4098121876				.
DFE	Degrees of Freedom for Error	499					.
DFM	Model Degrees of Freedom	34					.
DFT	Total Degrees of Freedom	533					.
DIV	Divisor for ASE	1066	266				.
ERR	Error Function	370.32103811	109.0100419				.
FPE	Final Prediction Error	0.1229828119					.
MAX	Maximum Absolute Error	0.9738751426	0.98640392				.
MSE	Mean Square Error	0.1156081812	0.1249985712				.
NOBS	Sum of Frequencies	533	133				.
NW	Number of Estimate Weights	34					.
RASE	Root Average Sum of Squares	0.3289886784	0.35355137				.
RFPE	Root Final Prediction Error	0.350689053					.
RMSE	Root Mean Squared Error	0.3400120309	0.35355137				.
SBC	Schwarz's Bayesian Criterion	583.79076653					.
SSE	Sum of Squared Errors	115.37696483	33.24961994				.
SUMW	Sum of Case Weights Times Freq	1066	266				.
MISC	Misclassification Rate	0.1519699812	0.1729323308				.
PROF	Total Profit for STATUS	268	65				.
APROF	Average Profit for STATUS	0.5028142589	0.4887218045				.

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
GENDER	1.142	.274	17.393	1	.000	3.134
MDD	.702	.311	5.094	1	.024	2.018
NDIR	-.482	.141	11.725	1	.001	.618
IND	.827	.370	4.989	1	.026	2.287
CONT	.456	.265	2.965	1	.085	1.578
CINA	1.200	.387	9.635	1	.002	3.320
INDIAN	2.058	.563	13.359	1	.000	7.828
MELAYU	1.367	.437	9.782	1	.002	3.925
CPI	-.123	.156	.625	1	.429	.884
GDP	.010	.046	.047	1	.828	1.010
BLR	3.106	2.503	1.540	1	.215	22.341
EMPY	2.790	1.927	2.096	1	.148	16.273
EBIT	.397	.385	1.065	1	.302	1.487
ROE	-1.151	.376	9.349	1	.002	.316
TLA	1.435	.244	34.699	1	.000	4.200
LTA	.308	.296	1.077	1	.299	1.360
CTA	-.232	.195	1.414	1	.234	.793
CLE	.113	.088	1.660	1	.198	1.120
LQT	-.083	.047	3.153	1	.076	.920
WCT	.018	.007	7.259	1	.007	1.018
NWC	.000	.000	1.391	1	.238	1.000
AST	-.013	.072	.034	1	.853	.987
EXP	-.033	.030	1.144	1	.285	.968
LogTA	.115	.066	3.001	1	.169	1.122
LogCAP	.054	.040	1.890	1	.083	1.056
AGE	-.168	.017	93.626	1	.000	.846
BLC	-.546	.263	4.305	1	.038	.579
Constant	1.311	1.354	.937	1	.333	3.711

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY, EBIT, ROE, TLA, LTA, CTA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC.

linktest

Iteration 0: log likelihood = -455.39694
Iteration 1: log likelihood = -236.13964
Iteration 2: log likelihood = -232.27156

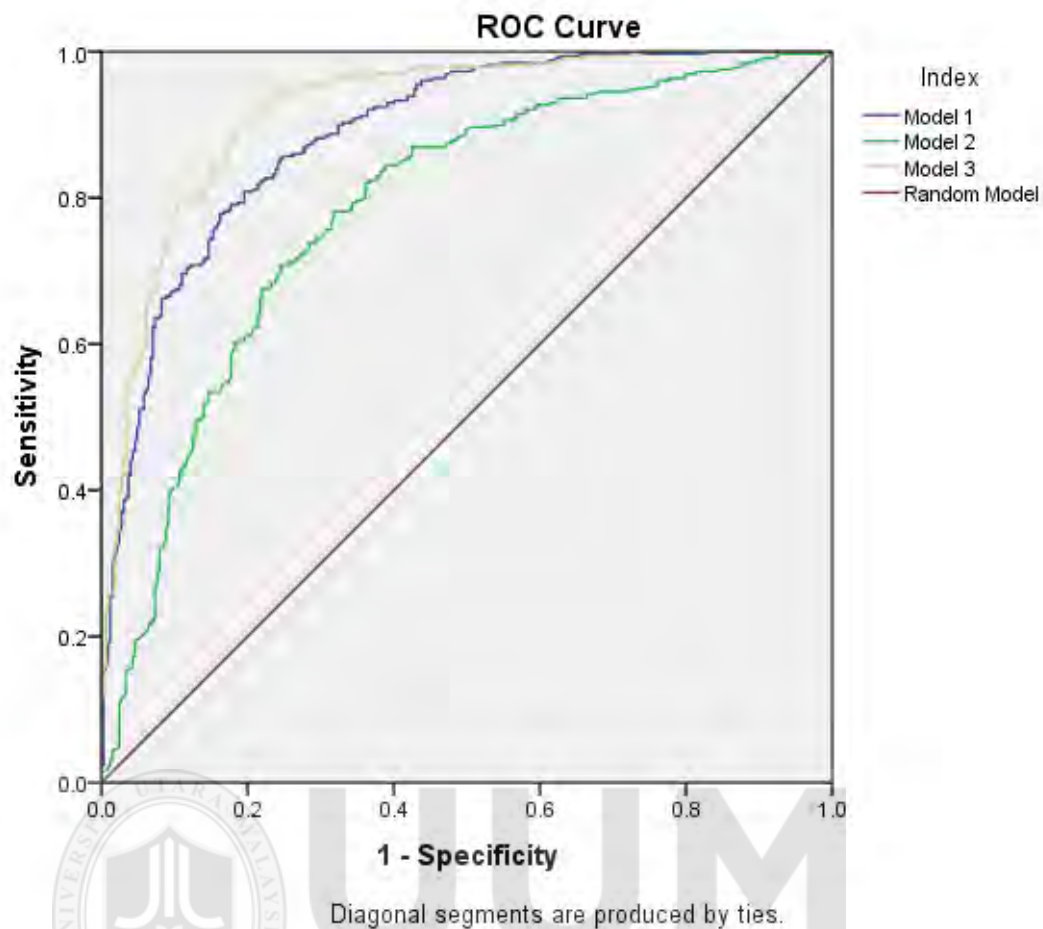
Logistic regression	Number of obs	=	657
	LR chi2(2)	=	446.78
	Prob > chi2	=	0.0000
Log likelihood = -232.00823	Pseudo R2	=	0.4905

```
brier status var29
```

Brier score	0.1100	
Spiegelhalter's z-statistic	-0.3571	p = 0.6395
Sanders-modified Brier score	0.1103	
Sanders resolution	0.1075	
Outcome index variance	0.2500	
Murphy resolution	0.1425	
Reliability-in-the-small	0.0029	
Forecast variance	0.1374	
Excess forecast variance	0.0605	
Minimum forecast variance	0.0769	
Reliability-in-the-large	0.0000	
2*Forecast-Outcome-Covar	0.2774	

Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Interval	
				Lower Bound	Upper Bound
Model 1	.888	.012	.000	.864	.913
Model 2	.783	.018	.000	.748	.819
Model 3	.921	.011	.000	.901	.942

b. Null hypothesis: true area = 0.5



APPENDIX 1d: Model 1 (2-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	223.111 ^a	.598	.797

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	19.403	8	.013

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-failed	Failed	
Step 1	STATUS Non-failed	214	21	91.1
	STATUS Failed	26	209	88.9
	Overall Percentage			90.0

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	
Step 1 ^a	EBIT	-6.407	1.212	27.969	1	.000	.002
	ROE	-.345	.165	4.381	1	.036	.708
	TLA	3.912	.599	42.623	1	.000	50.010
	LTA	-1.857	1.118	2.760	1	.097	.156
	CTA	.590	.270	4.788	1	.029	1.805
	CLE	.077	.061	1.630	1	.202	1.081
	LQT	-.593	.398	2.220	1	.136	.553
	WCT	.620	.407	2.325	1	.127	1.859
	NWC	.024	.011	5.822	1	.016	1.000
	AST	-.032	.102	.099	1	.754	.969
	EXP	-.002	.019	.009	1	.925	.998
	LogTA	.076	.110	.487	1	.485	1.079
	LogCAP	.125	.055	5.121	1	.024	1.134
	AGE	-.159	.024	43.294	1	.000	.853
	BLC	-.401	.379	1.119	1	.290	.670
	Constant	-3.026	1.692	3.198	1	.074	.049

a. Variable(s) entered on step 1: EBIT, ROE, TLA, LTA, CTA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC.

linktest

Iteration 0: log likelihood = -325.77917
 Iteration 1: log likelihood = -129.03169
 Iteration 2: log likelihood = -120.41721
 Iteration 3: log likelihood = -110.37363
 Iteration 4: log likelihood = -109.98733
 Iteration 5: log likelihood = -109.98643
 Iteration 6: log likelihood = -109.98642

Logistic regression

Number of obs = 470
 LR chi2(2) = 431.59
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.6624

Log likelihood = -109.98642

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.017407	.108106	9.41	0.000	.8055234	1.229291
_hatsq	-.0213964	.0037266	-5.74	0.081	-.0287005	-.0140923
_cons	.056562	.1711062	0.33	0.741	-.2788	.3919241

brier status var27

Mean probability of outcome 0.5000
 of forecast 0.5000

Correlation 0.8482
ROC area 0.9675 p = 0.0000

Brier score 0.0701
Spiegelhalter's z-statistic -0.6123 p = 0.7298
Sanders-modified Brier score 0.0723
Sanders resolution 0.0719
Outcome index variance 0.2500
Murphy resolution 0.1781
Reliability-in-the-small 0.0004
Forecast variance 0.1757
Excess forecast variance 0.0493
Minimum forecast variance 0.1264
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.3555

APPENDIX 1e: Model 2 (2-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	491.568 ^a	.289	.385

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	19.120	8	.014

Classification Table^a

	Observed	Predicted			
		STATUS		Percentage Correct	
		Non-failed	Failed		
Step 1	STATUS Non-failed	170	65	72.3	
	Failed	41	194	82.6	
	Overall Percentage			77.4	

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a	GENDER	1.258	.257	23.899	1	.000	3.518
	MDD	.615	.309	3.978	1	.046	1.850
	NDIR	-1.097	.158	48.523	1	.000	.334
	IND	.361	.308	1.376	1	.241	1.435
	CONT	.948	.244	15.061	1	.000	2.581
	CINA	.584	.358	2.662	1	.103	1.794
	INDIAN	1.673	.526	10.121	1	.001	5.329
	MELAYU	1.151	.415	7.680	1	.006	3.161
	CPI	.019	.142	.018	1	.893	1.019

GDP	.055	.042	1.690	1	.194	1.056
BLR	2.278	2.661	.733	1	.392	9.760
EMPY	-2.087	1.987	1.103	1	.294	.124
Constant	.544	.599	.824	1	.364	1.722

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY.

linktest

Iteration 0: log likelihood = -325.77917
Iteration 1: log likelihood = -244.54564
Iteration 2: log likelihood = -244.39823
Iteration 3: log likelihood = -244.39657
Iteration 4: log likelihood = -244.39657

Logistic regression

Number of obs = 470
LR chi2(2) = 162.77
Prob > chi2 = 0.0000
Pseudo R2 = 0.2498

Log likelihood = -244.39657

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.040994	.1025262	10.15	0.000	.8400462 1.241942
_hatsq	.0817878	.036761	2.22	0.126	.0097376 .153838
_cons	-.1069528	.1222062	-0.88	0.381	-.3464725 .132567

brier status var28

Mean probability of outcome 0.5000
of forecast 0.5000

Correlation 0.5675
ROC area 0.8270 p = 0.0000

Brier score 0.1696
Spiegelhalter's z-statistic -0.5695 p = 0.7155
Sanders-modified Brier score 0.1711
Sanders resolution 0.1659
Outcome index variance 0.2500
Murphy resolution 0.0841
Reliability-in-the-small 0.0052
Forecast variance 0.0755
Excess forecast variance 0.0512
Minimum forecast variance 0.0243
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.1559

APPENDIX 1f: Model 3 (2-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	154.985 ^a	.652	.870

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	88.360	8	.000

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-failed	Failed	
Step 1	STATUS Non-failed	221	14	94.0
	STATUS Failed	17	218	92.8
	Overall Percentage			93.4

a. The cut value is .500

Model	Estimates	Plot	Statistics	Code	Log	Output	Notes
Fit Statistic	Label		Training	Validation	Test		
AIC	Akaike's Information Criterion		191.76525252	.	.		
ASE	Average Squared Error		0.04343353	0.0592007858	.		
AVERR	Average Error Function		0.1619218783	0.2022459027	.		
DFE	Degrees of Freedom for Error		341	.	.		
DFM	Model Degrees of Freedom		35	.	.		
DFT	Total Degrees of Freedom		376	.	.		
DIV	Divisor for ASE		752	188	.		
ERR	Error Function		121.76525252	38.022229704	.		
FPE	Final Prediction Error		0.0523495039	.	.		
MAX	Maximum Absolute Error		0.9998954887	0.9813912625	.		
MSE	Mean Square Error		0.0478915169	0.0592007858	.		
NOBS	Sum of Frequencies		376	94	.		
NW	Number of Estimate Weights		35	.	.		
RASE	Root Average Sum of Squares		0.2084071256	0.2433121161	.		
RFPE	Root Final Prediction Error		0.2288001396	.	.		
RMSE	Root Mean Squared Error		0.2188413054	0.2433121161	.		
SBC	Schwarz's Bayesian Criterion		329.30087254	.	.		
SSE	Sum of Squared Errors		32.662014551	11.129747736	.		
SUMW	Sum of Case Weights Times Freq		752	188	.		
MISC	Misclassification Rate		0.0585106383	0.0744680851	.		
PROF	Total Profit for STATUS		189	46	.		
APROF	Average Profit for STATUS		0.5026595745	0.4893617021	.		

Variables in the Equation

		Variables in the Equation					
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a	GENDER	1.241	.528	5.518	1	.019	3.460
	MDD	1.415	.618	5.243	1	.022	4.116
	NDIR	-1.575	.337	21.791	1	.000	.207
	IND	.876	.684	1.640	1	.200	2.402
	CONT	.977	.496	3.878	1	.049	2.656
	CINA	-.509	.720	.500	1	.479	.601
	INDIAN	-.060	1.014	.004	1	.953	.942
	MELAYU	-.111	.850	.017	1	.897	.895
	CPI	.117	.290	.162	1	.687	1.124
	GDP	-.012	.088	.017	1	.895	.988
	BLR	2.187	5.011	.190	1	.663	8.907
	EMPY	-4.257	4.044	1.108	1	.292	.014
	EBIT	-6.770	1.561	18.819	1	.000	.001
	ROE	-.268	.228	1.386	1	.239	.765
	TLA	4.534	.780	33.762	1	.000	93.091
	LTA	-3.399	1.484	5.247	1	.022	.033
	CTA	.618	.334	3.424	1	.064	1.856
	CLE	.100	.080	1.571	1	.210	1.106

LQT	-.983	.537	3.355	1	.067	.374
WCT	1.058	.545	3.771	1	.052	2.880
NWC	.580	.320	2.975	1	.085	1.000
AST	.003	.025	.019	1	.890	1.003
EXP	.012	.021	.309	1	.578	1.012
LogTA	.133	.125	1.124	1	.289	1.142
LogCAP	.116	.063	3.355	1	.067	1.123
AGE	-.168	.032	28.239	1	.000	.845
BLC	-.747	.496	2.274	1	.132	.474
Constant	-1.023	2.369	.186	1	.666	.359

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY, EBIT, ROE, TLA, LTA, CTA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC.

linktest

Iteration 0: log likelihood = -325.77917
Iteration 1: log likelihood = -76.387427
Iteration 2: log likelihood = -75.92187
Iteration 3: log likelihood = -75.894544
Iteration 4: log likelihood = -75.894017
Iteration 5: log likelihood = -75.894016

Logistic regression

Number of obs = 470
LR chi2(2) = 499.77
Prob > chi2 = 0.0000
Pseudo R2 = 0.7670

Log likelihood = -75.894016

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.0234	.1163551	8.80	0.000	.7953481	1.251452
_hatsq	-.0189316	.0032175	-5.88	0.121	-.0252378	-.0126254
_cons	.066105	.2098488	0.32	0.753	-.345191	.4774011

brier status var29

Mean probability of outcome
of forecast 0.5000

Correlation 0.9050
ROC area 0.9841 p = 0.0000

Brier score 0.0453
Spiegelhalter's z-statistic -0.7383 p = 0.7698
Sanders-modified Brier score 0.0507
Sanders resolution 0.0502
Outcome index variance 0.2500
Murphy resolution 0.1998
Reliability-in-the-small 0.0005
Forecast variance 0.2002
Excess forecast variance 0.0362
Minimum forecast variance 0.1640
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.4049

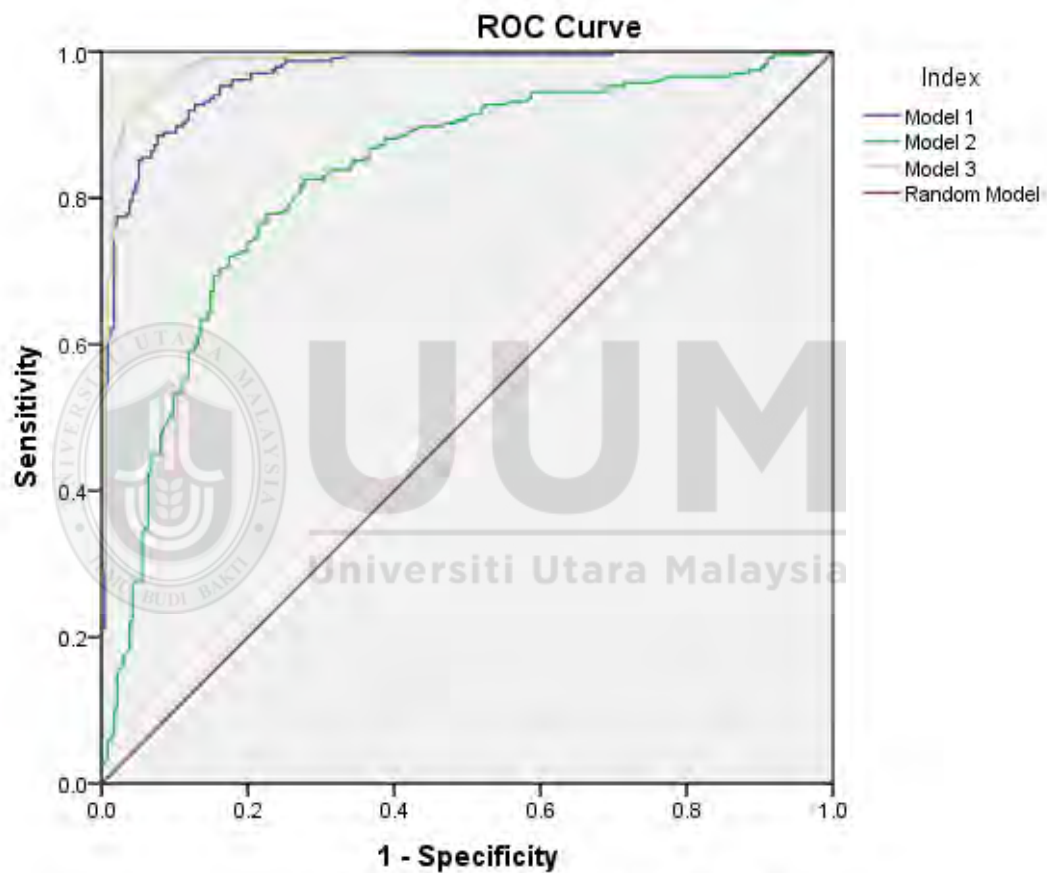
ROC Curve 2 year sub-sample models

Test Result Variable(s)	Area Under the Curve				
	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Model 1	.968	.007	.000	.954	.981
Model 2	.827	.019	.000	.789	.865
Model 3	.984	.005	.000	.975	.993

The test result variable(s): Model 2 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5



Diagonal segments are produced by ties.

APPENDIX 1g: Model 1 (1-Year Prior Sub-sample)

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	244.011 ^a	.553	.737

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.443	8	.598

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	183	27	87.1
	Failed	19	191	91.0
	Overall Percentage			89.0

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	
Step 1 ^a	EBIT	-.257	.422	.370	1	.543	.774
	ROE	-.432	.107	16.209	1	.000	.649
	TLA	1.200	.350	11.739	1	.001	3.321
	LTA	-.172	.620	.077	1	.781	.842
	CTA	-.068	.425	.026	1	.873	.934
	CLE	.284	.114	6.242	1	.012	1.328
	LQT	-.864	.239	13.062	1	.000	.421
	WCT	.756	.239	10.030	1	.002	2.131
	NWC	.000	.000	1.013	1	.314	1.000
	AST	-2.404	.372	41.651	1	.000	.090
	EXP	-.701	.359	3.820	1	.051	.496
	LogTA	.140	.099	1.984	1	.159	1.150
	LogCAP	-.034	.071	.223	1	.637	.967
	AGE	-.124	.019	44.777	1	.000	.883
	BLC	-.712	.377	3.576	1	.059	.490
	Constant	3.991	1.330	8.998	1	.003	54.105

a. Variable(s) entered on step 1: EBIT, ROE, TLA, LTA, CTA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC.

linktest

```
Iteration 0: log likelihood = -291.12182
Iteration 1: log likelihood = -123.35153
Iteration 2: log likelihood = -122.06682
Iteration 3: log likelihood = -121.92007
Iteration 4: log likelihood = -121.89403
Iteration 5: log likelihood = -121.89386
Iteration 6: log likelihood = -121.89386
```

Logistic regression

```
Number of obs    =      420
LR chi2(2)       =    338.46
Prob > chi2      =    0.0000
Pseudo R2       =    0.5813
```

Log likelihood = -121.89386

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.002409	.101132	9.91	0.000	.8041943 1.200625
_hatsq	.0185495	.0381774	0.49	0.627	-.0562767 .0933758

_cons | -.0496087 .1943761 -0.26 0.799 -.4305789 .3313616

brier status var27

Mean probability of outcome 0.5000
of forecast 0.5000

Correlation 0.8048
ROC area 0.9479 p = 0.0000

Brier score 0.0881
Spiegelhalter's z-statistic -0.2876 p = 0.6132
Sanders-modified Brier score 0.0874
Sanders resolution 0.0863
Outcome index variance 0.2500
Murphy resolution 0.1637
Reliability-in-the-small 0.0011
Forecast variance 0.1595
Excess forecast variance 0.0562
Minimum forecast variance 0.1033
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.3215

APPENDIX 1h: Model 2 (1-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	418.674 ^a	.321	.428

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	14.217	8	.250

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	162	48	77.1
	Failed	48	161	77.0
	Overall Percentage			77.1

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
GENDER	1.207	.285	17.902	1	.000	3.344
MDD	1.429	.310	21.189	1	.000	4.175
NDIR	-.893	.166	28.983	1	.000	.409
IND	.529	.337	2.458	1	.117	1.697
CONT	.856	.259	10.892	1	.001	2.354
CINA	.659	.410	2.582	1	.108	1.933
INDIAN	1.527	.576	7.022	1	.008	4.603
MELAYU	1.398	.467	8.954	1	.003	4.047
CPI	.296	.170	3.034	1	.082	1.345
GDP	.125	.057	4.786	1	.029	1.133
BLR	2.995	2.706	1.225	1	.268	19.985
EMPY	4.065	1.333	9.298	1	.002	58.268
Constant	-.156	.661	.056	1	.813	.855

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY.

linktest

Iteration 0: log likelihood = -290.42748
Iteration 1: log likelihood = -209.94448
Iteration 2: log likelihood = -209.34503
Iteration 3: log likelihood = -209.32896
Iteration 4: log likelihood = -209.32896

Logistic regression Number of obs = 419
LR chi2(2) = 162.20
Prob > chi2 = 0.0000
Log likelihood = -209.32896 Pseudo R2 = 0.2792

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.000267	.1012978	9.87	0.000	.8017267 1.198807
_hatsq	.0076864	.0608362	0.13	0.899	-.1115504 .1269231
_cons	-.0108247	.1476234	-0.07	0.942	-.3001612 .2785118

brier status var28

Mean probability of outcome 0.4988
of forecast 0.4988

Correlation 0.5935
ROC area 0.8397 p = 0.0000

Brier score 0.1620
Spiegelhalter's z-statistic -0.3587 p = 0.6401
Sanders-modified Brier score 0.1629
Sanders resolution 0.1596
Outcome index variance 0.2500
Murphy resolution 0.0904
Reliability-in-the-small 0.0032
Forecast variance 0.0847
Excess forecast variance 0.0549
Minimum forecast variance 0.0298
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.1727

APPENDIX 1i: Model 3 (1-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	174.905 ^a	.620	.827

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	11.691	8	.132

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed	
Step 1	STATUS Non-Failed	191	19	91.0
	STATUS Failed	17	192	91.9
	Overall Percentage			91.4

a. The cut value is .500

Model	Estimates	Plot	Statistics	Code	Log	Output	Notes
Fit Statistic	Label	Training	Validation	Test			
AIC	Akaike's Information Criterion	187.40235566	.	.			.
ASE	Average Squared Error	0.0497072516	0.1169838215	.			.
AVERR	Average Error Function	0.1806582674	0.5148348786	.			.
DFE	Degrees of Freedom for Error	303	.	.			.
DFM	Model Degrees of Freedom	33	.	.			.
DFT	Total Degrees of Freedom	336	.	.			.
DIV	Divisor for ASE	672	168	.			.
ERR	Error Function	121.40235566	86.492259601	.			.
FPE	Final Prediction Error	0.0605345738	.	.			.
MAX	Maximum Absolute Error	0.998097095	0.9999918695	.			.
MSE	Mean Square Error	0.0551209127	0.1169838215	.			.
NOBS	Sum of Frequencies	336	84	.			.
NW	Number of Estimate Weights	33	.	.			.
RASE	Root Average Sum of Squares	0.2229512315	0.3420289775	.			.
RFPE	Root Final Prediction Error	0.2460377486	.	.			.
RMSE	Root Mean Squared Error	0.2347784332	0.3420289775	.			.
SBC	Schwarz's Bayesian Criterion	313.36702394	.	.			.
SSE	Sum of Squared Errors	33.40327309	19.653282008	.			.
SUMW	Sum of Case Weights Times Freq	672	168	.			.
MISC	Misclassification Rate	0.0654761905	0.1666666667	.			.
PROF	Total Profit for STATUS	166	44	.			.
APROF	Average Profit for STATUS	0.494047619	0.5238095238	.			.

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a						
GENDER	1.112	.464	5.745	1	.017	3.040
MDD	2.044	.558	13.437	1	.000	7.725
NDIR	-.578	.222	6.769	1	.009	.561
IND	.133	.619	.046	1	.830	1.142
CONT	.862	.443	3.784	1	.052	2.368
CINA	1.098	.726	2.289	1	.130	2.999
INDIAN	2.765	1.025	7.276	1	.007	15.873
MELAYU	2.421	.858	7.957	1	.005	11.259
CPI	.349	.292	1.434	1	.231	1.418
GDP	.145	.090	2.617	1	.106	1.156
BLR	-4.834	4.729	1.045	1	.307	.008
EMPY	-.115	2.230	.003	1	.959	.891
EBIT	-.354	.458	.597	1	.440	.702
ROE	-.505	.131	14.850	1	.000	.604
TLA	1.095	.425	6.649	1	.010	2.988
LTA	-.417	.779	.286	1	.592	.659
CTA	.580	.619	.878	1	.349	1.785
CLE	.265	.141	3.510	1	.061	1.303
LQT	-1.087	.271	16.080	1	.000	.337
WCT	.940	.265	12.596	1	.000	2.561
NWC	.106	.410	2.769	1	.096	1.000
AST	-2.615	.472	30.669	1	.000	.073
EXP	-.846	.511	2.742	1	.098	.429
LogTA	.135	.122	1.227	1	.268	1.144
LogCAP	.031	.097	.101	1	.750	1.031
AGE	-.131	.025	28.423	1	.000	.877
BLC	-1.039	.495	4.401	1	.036	.354
Constant	1.914	1.963	.951	1	.329	6.783

a. Variable(s) entered on step 1: GENDER, MDD, NDIR, IND, CONT, CINA, INDIAN, MELAYU, CPI, GDP, BLR, EMPY, EBIT, ROE, TLA, LTA, CTA, CLE, LQT, WCT, NWC, AST, EXP, LogTA, LogCAP, AGE, BLC.

linktest

Iteration 0: log likelihood = -290.42748
Iteration 1: log likelihood = -88.918037
Iteration 2: log likelihood = -87.904237
Iteration 3: log likelihood = -87.408675
Iteration 4: log likelihood = -87.370513
Iteration 5: log likelihood = -87.370426
Iteration 6: log likelihood = -87.370426

Logistic regression

Number of obs = 419
LR chi2(2) = 406.11
Prob > chi2 = 0.0000
Pseudo R2 = 0.6992

Log likelihood = -87.370426

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.00981	.1153383	8.76	0.000	.7837507 1.235869
_hatsq	-.0157248	.0389211	-0.40	0.686	-.0920088 .0605592
_cons	.0470808	.2264335	0.21	0.835	-.3967207 .4908823

brier status var29

Mean probability of outcome 0.4988
of forecast 0.4988

Correlation 0.8714

ROC area 0.9733 p = 0.0000

Brier score 0.0602

Spiegelhalter's z-statistic -0.5069 p = 0.6939

Sanders-modified Brier score 0.0629

Sanders resolution 0.0619

Outcome index variance 0.2500

Murphy resolution 0.1881

Reliability-in-the-small 0.0010

Forecast variance 0.1862

Excess forecast variance 0.0448

Minimum forecast variance 0.1414

Reliability-in-the-large 0.0000

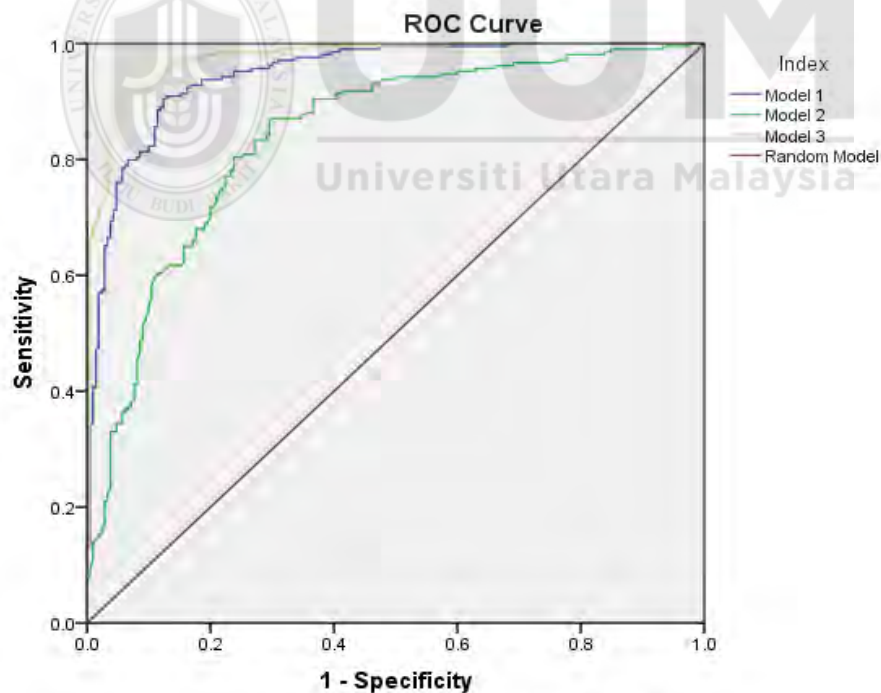
2*Forecast-Outcome-Covar 0.3760

ROC Curve 1 year sub-sample models

Area Under the Curve					
Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Model 1	.948	.010	.000	.928	.968
Model 2	.840	.020	.000	.801	.878
Model 3	.973	.007	.000	.960	.987

The test result variable(s): Model 2 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

- a. Under the nonparametric assumption
- b. Null hypothesis: true area = 0.5



Diagonal segments are produced by ties.

APPENDIX 2a: 3-year Prior to bankruptcy sample endogeneity test

Model 2

NDIR

First-stage regressions

```
reg ndir gender mdd ind cont e1 e3 e4 cpi gdp blr empy l_ind_ndir
```

Source	SS	df	MS	Number of obs =	657
Model	45.4966414	12	3.79138678	F(12, 644) =	4.70
Residual	519.611426	644	.80685004	Prob > F =	0.0000
				R-squared =	0.0805
				Adj R-squared =	0.0634
Total	565.108067	656	.861445224	Root MSE =	.89825

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	-.3183718	.0789679	-4.03	0.000	-.4734375 -.1633061
mdd	-.1591371	.0909928	-1.75	0.081	-.3378156 .0195414
ind	.2900705	.1027506	2.82	0.005	.0883039 .4918371
cont	.0081399	.079135	0.10	0.918	-.147254 .1635338
e1	-.289323	.1110966	-2.60	0.009	-.5074783 -.0711677
e3	-.0619091	.1647978	-0.38	0.707	-.3855151 .2616969
e4	-.0752404	.1279666	-0.59	0.557	-.3265227 .1760419
cpi	-.0183934	.0470557	-0.39	0.696	-.1107945 .0740076
gdp	-.011658	.0138528	-0.84	0.400	-.0388601 .0155442
blr	.6909678	.7398639	0.93	0.351	-.7618693 2.143805
empy	-.1780719	.5153023	-0.35	0.730	-1.189948 .8338039
l_ind_ndir	.0497341	.0286848	1.73	0.083	-.006593 .1060612
_cons	2.831024	.169401	16.71	0.000	2.498379 3.163669

. predict ndirH
(option xb assumed; fitted values)
(9 missing values generated)

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .055955 (p = 0.8130)
Wu-Hausman F(1,643) = .054767 (p = 0.8150)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .140325 (p = 0.7080)
Basman chi2(1) = .137364 (p = 0.7109)

MDD

First-stage regressions

```
. reg mdd gender ndir ind cont e1 e3 e4 cpi gdp blr empy l_dirown
```

Source	SS	df	MS	Number of obs =	657
Model	23.5783098	12	1.96485915	F(12, 644) =	13.05
Residual	96.9422382	644	.150531426	Prob > F =	0.0000
				R-squared =	0.1956
				Adj R-squared =	0.1806
Total	120.520548	656	.183720347	Root MSE =	.38798

mdd	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----	-------	-----------	---	------	----------------------

gender		.0828058	.0343565	2.41	0.016	.0153416	.15027
ndir		-.0284473	.0169462	-1.68	0.094	-.0617237	.0048291
ind		-.3326505	.0427448	-7.78	0.000	-.4165866	-.2487145
cont		.2617919	.032469	8.06	0.000	.198034	.3255498
e1		.1862554	.0477674	3.90	0.000	.0924566	.2800541
e3		.0466491	.0711427	0.66	0.512	-.0930505	.1863488
e4		.2039544	.0547257	3.73	0.000	.0964921	.3114167
cpi		.0090256	.0203374	0.44	0.657	-.0309101	.0489613
gdp		.0130674	.0059645	2.19	0.029	.0013552	.0247797
blr		-.0891349	.3198464	-0.28	0.781	-.7172028	.5389329
empy		-.2650757	.2224095	-1.19	0.234	-.7018111	.1716597
l_dirown		.0559787	.0558628	1.00	0.017	-.0537165	.1656739
_cons		-.0041954	.0831959	-0.05	0.960	-.1675634	.1591726

. predict mddH
(option xb assumed; fitted values)
(9 missing values generated)

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .125913 (p = 0.7227)
Wu-Hausman F(1,643) = .123254 (p = 0.7256)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = 1.48513 (p = 0.2230)
Basmann chi2(1) = 1.45678 (p = 0.2274)

Model 3

NDIR

First-stage regressions

Instrumental variables (2SLS) regression

Number of obs = 657

Wald chi2(27) = 537.74
Prob > chi2 = 0.0000
R-squared = 0.4424
Root MSE = .37335

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
ndir		-.160868	.1354521	-1.19	0.235	-.4263493 .1046133
ebit		.0466446	.0485141	0.96	0.336	-.0484413 .1417306
roe		-.0887897	.0349754	-2.54	0.011	-.1573402 -.0202392
tla		.1269728	.0235558	5.39	0.000	.0808043 .1731413
lta		.0342624	.0421189	0.81	0.416	-.0482891 .1168138
cta		-.0309136	.0258947	-1.19	0.233	-.0816663 .0198392
cle		.0168944	.011215	1.51	0.132	-.0050867 .0388754
lqt		-.0028995	.0044988	-0.64	0.519	-.0117169 .0059179
wct		.0005068	.0011611	0.44	0.663	-.0017689 .0027824
nwc		-1.46e-09	2.83e-09	-0.52	0.606	-7.00e-09 4.09e-09
ast		-.000488	.0095428	-0.05	0.959	-.0191915 .0182155
exp		-.0009173	.0053399	-0.17	0.864	-.0113833 .0095488
logta		.0123439	.008771	1.41	0.159	-.0048469 .0295348
logcap		.0111465	.0049514	2.25	0.024	.0014419 .0208511
age		-.0140345	.0021669	-6.48	0.000	-.0182815 -.0097875
blc		-.0425748	.0332567	-1.28	0.200	-.1077568 .0226071
gender		.156609	.0521476	3.00	0.003	.0544016 .2588165
mdd		.0763106	.0426984	1.79	0.074	-.0073767 .159998
ind		.0955238	.0536835	1.78	0.075	-.0096939 .2007416
cont		.0893685	.0351633	2.54	0.011	.0204496 .1582873
cpi		-.0117918	.019865	-0.59	0.553	-.0507265 .027143
gdp		.0043141	.0060419	0.71	0.475	-.0075279 .0161561
blr		.5049953	.3173674	1.59	0.112	-.1170333 1.127024
empy		.3073889	.2171206	1.42	0.157	-.1181598 .7329375
e1		-.0477121	.0526516	-0.91	0.365	-.1509074 .0554832

```

      e2 |  -.2475615   .053905   -4.59   0.000   -.3532134   -.1419096
      e3 |  .0901995   .0656428    1.37   0.169   -.038458   .218857
      _cons |  .8625341   .3593447    2.40   0.016   .1582315   1.566837
-----+-----
Instrumented:  ndir
Instruments:   ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age
               blc gender mdd ind cont cpi gdp blr emp e1 e2 e3 l_ind_ndir
               l_tngasset

. estat endog
  Tests of endogeneity
  Ho: variables are exogenous
  Durbin (score) chi2(1)      =  .509884   (p = 0.4752)
  Wu-Hausman F(1,628)        =  .487756   (p = 0.4852)

. estat overid
  Tests of overidentifying restrictions:
  Sargan (score) chi2(1) =  .039963   (p = 0.8416)
  Basman chi2(1)      =  .038201   (p = 0.8450)

```

MDD

First-stage regressions

```

Instrumental variables (2SLS) regression
Number of obs =      657
Wald chi2(27) =    487.17
Prob > chi2    =    0.0000
R-squared      =    0.3737
Root MSE      =    .3957

```

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
mdd	-.3245251	.698302	-0.46	0.642	-1.693172	1.044122
ebit	.0700524	.0661006	1.06	0.289	-.0595023	.1996072
roe	-.1271836	.0764011	-1.66	0.096	-.276927	.0225598
tla	.1563216	.0439972	3.55	0.000	.0700888	.2425545
lta	.043295	.0404204	1.07	0.284	-.0359275	.1225174
cta	-.052167	.045197	-1.15	0.248	-.1407516	.0364176
cle	.0123297	.0098602	1.25	0.211	-.0069959	.0316554
lqt	-.003412	.0053136	-0.64	0.521	-.0138265	.0070026
wct	.0000868	.0016698	0.05	0.959	-.003186	.0033596
nwc	-1.86e-09	2.79e-09	-0.67	0.505	-7.34e-09	3.61e-09
ast	-.0041021	.0108417	-0.38	0.705	-.0253515	.0171472
exp	-.0051393	.0085543	-0.60	0.548	-.0219054	.0116268
logta	.0112014	.009039	1.24	0.215	-.0065146	.0289175
logcap	.013377	.0070625	1.89	0.058	-.0004651	.0272192
age	-.0156771	.001463	-10.72	0.000	-.0185445	-.0128098
blc	-.0783448	.059256	-1.32	0.186	-.1944844	.0377949
gender	.2138105	.062193	3.44	0.001	.0919144	.3357065
ndir	-.0771101	.0245281	-3.14	0.002	-.1251842	-.0290359
ind	-.0666609	.2425222	-0.27	0.783	-.5419957	.4086739
cont	.180771	.1697951	1.06	0.287	-.1520212	.5135632
cpi	-.0067974	.0214234	-0.32	0.751	-.0487864	.0351916
gdp	.0102887	.010249	1.00	0.315	-.0097988	.0303763
blr	.4301503	.3313222	1.30	0.194	-.2192294	1.07953
empy	.2234104	.2814882	0.79	0.427	-.3282964	.7751172
e1	-.0285335	.0428507	-0.67	0.505	-.1125194	.0554523
e2	-.3331586	.1533184	-2.17	0.030	-.6336571	-.0326601
e3	.0275959	.1186818	0.23	0.816	-.2050161	.2602078
_cons	.7948477	.3133716	2.54	0.011	.1806507	1.409045

```

Instrumented:  mdd
Instruments:   ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age
               blc gender ndir ind cont cpi gdp blr empy e1 e2 e3 l_dirown
               l_tngasset

. estat endog
  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)      =  .413483   (p = 0.5202)
  Wu-Hausman F(1,628)        =  .395481   (p = 0.5297)

. estat overid
  Tests of overidentifying restrictions:
  Sargan (score) chi2(1) =  .405881   (p = 0.5241)

```

Basmann chi2(1) = .388205 (p = 0.5332)

IND

First-stage regressions

						Number of obs = 657
						F(28, 628) = 7.61
						Prob > F = 0.0000
						R-squared = 0.2533
						Adj R-squared = 0.2200
						Root MSE = 0.3362
ind	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ebit	-.0026062	.0437502	-0.06	0.953	-.0885206	.0833083
roe	-.0384971	.0314626	-1.22	0.222	-.1002817	.0232874
tla	.0158607	.0192287	0.82	0.410	-.0218997	.0536211
lta	.0314216	.0338779	0.93	0.354	-.0351061	.0979493
cta	-.0221761	.0233317	-0.95	0.342	-.0679937	.0236415
cle	-.0035337	.0083753	-0.42	0.673	-.0199806	.0129133
lqt	.0017103	.003689	0.46	0.643	-.0055341	.0089546
wct	-.0016322	.0009696	-1.68	0.093	-.0035364	.0002719
nwc	-1.07e-09	2.28e-09	-0.47	0.637	-5.54e-09	3.40e-09
ast	-.0064165	.0085112	-0.75	0.451	-.0231304	.0102974
exp	-.0046153	.004777	-0.97	0.334	-.0139962	.0047655
logta	.0291712	.0075818	3.85	0.000	.0142825	.0440599
logcap	-.0032949	.0043888	-0.75	0.453	-.0119133	.0053236
age	.0025001	.0011003	2.27	0.023	.0003394	.0046607
blc	-.0153561	.0286485	-0.54	0.592	-.0716146	.0409024
gender	.0700927	.030829	2.27	0.023	.0095524	.1306331
mdd	-.2686871	.0335514	-8.01	0.000	-.3345736	-.2028006
ndir	.0313954	.0151824	2.07	0.039	.0015811	.0612098
cont	.2250367	.0290343	7.75	0.000	.1680207	.2820528
cpi	.0529498	.0176377	3.00	0.003	.0183138	.0875857
gdp	.0155901	.0052062	2.99	0.003	.0053665	.0258137
blr	-.2896817	.2801697	-1.03	0.302	-.8398645	.2605012
empy	.2311989	.1992909	1.16	0.246	-.1601583	.622556
e1	-.0969109	.0355142	-2.73	0.007	-.1666518	-.02717
e2	-.0009026	.048537	-0.02	0.985	-.0962169	.0944118
e3	-.0604715	.0587721	-1.03	0.304	-.1758852	.0549422
l_ind_ind	-.0627315	.0739917	-0.85	0.397	-.2080326	.0825697
l_tngasset	.0521752	.0345788	1.51	0.132	-.0157289	.1200793
_cons	-.2281275	.1385373	-1.65	0.100	-.5001798	.0439248

Instrumental variables (2SLS) regression

Number of obs = 657
Wald chi2(27) = 565.82
Prob > chi2 = 0.0000
R-squared = 0.4587
Root MSE = .36787

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ind	-.0765755	.6167688	-0.12	0.901	-1.28542	1.132269
ebit	.0457692	.0477921	0.96	0.338	-.0479015	.13944
roe	-.0936576	.0423698	-2.21	0.027	-.1767009	-.0106142
tla	.1364737	.0233722	5.84	0.000	.090665	.1822825
lta	.0529559	.0428937	1.23	0.217	-.0311142	.137026
cta	-.0339629	.0284135	-1.20	0.232	-.0896524	.0217265
cle	.0119626	.0094421	1.27	0.205	-.0065435	.0304687
lqt	-.0012808	.0042205	-0.30	0.762	-.0095527	.0069912
wct	.0005587	.001471	0.38	0.704	-.0023243	.0034417
nwc	-2.58e-09	2.63e-09	-0.98	0.327	-7.74e-09	2.58e-09
ast	-.0027243	.0103694	-0.26	0.793	-.0230479	.0175992
exp	-.0020284	.0059701	-0.34	0.734	-.0137296	.0096729
logta	.0153171	.0199882	0.77	0.443	-.0238591	.0544933
logcap	.0100358	.0051911	1.93	0.053	-.0001385	.0202102
age	-.0149018	.0019588	-7.61	0.000	-.0187409	-.0110626
blc	-.0522503	.0332979	-1.57	0.117	-.117513	.0130124
gender	.1947056	.055408	3.51	0.000	.0861078	.3033034
mdd	.0481744	.1683397	0.29	0.775	-.2817653	.3781142
ndir	-.0621835	.0262963	-2.36	0.018	-.1137233	-.0106437
cont	.116373	.1422635	0.82	0.413	-.1624583	.3952042
cpi	-.0020888	.0368165	-0.06	0.955	-.0742478	.0700702
gdp	.0077872	.0111541	0.70	0.485	-.0140745	.0296489

```

      blr | .4074534 .3653917 1.12 0.265 -.3087013 1.123608
      empy | .3462222 .2382988 1.45 0.146 -.1208348 .8132792
      e1 | -.0379354 .0704552 -0.54 0.590 -.176025 .1001542
      e2 | -.2487437 .0530846 -4.69 0.000 -.3527877 -.1446998
      e3 | .0749539 .0756484 0.99 0.322 -.0733144 .2232221
      _cons | .5966113 .2148678 2.78 0.005 .1754782 1.017744
-----+-----
Instrumented: ind
Instruments: ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age
             blc gender mdd ndir cont cpi gdp blr empy e1 e2 e3 l_ind_ind
             l_tngasset

. estat endog, forcenonrobust
  Tests of endogeneity
  Ho: variables are exogenous
  Durbin (score) chi2(1) = .061245 (p = 0.8045)
  Wu-Hausman F(1,628) = .058547 (p = 0.8089)

. estat overid
  Tests of overidentifying restrictions:
  Sargan (score) chi2(1) = .035078 (p = 0.8514)
  Basman chi2(1) = .033532 (p = 0.8547)

```

APPENDIX 2b: 2- year prior to bankruptcy sample endogeneity test

Model 2

NDIR

First-stage regressions

```

reg ndir gender mdd ind cont e1 e3 e4 cpi gdp blr empy l_ind ndir

      Source |      SS      df      MS      Number of obs =      470
-----+-----+-----+-----+----- F( 12, 457) =      3.34
      Model |    43.23143      12    3.60261917 Prob > F      =    0.0001
      Residual |   493.034527     457    1.07885017 R-squared      =    0.0806
-----+-----+-----+-----+----- Adj R-squared =    0.0565
      Total |   536.265957     469    1.14342422 Root MSE      =    1.0387

```

```

-----+-----
      ndir |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----+-----+-----+-----+-----
      gender |   -.2853706   .1083013    -2.63   0.009   -.4982009   -.0725404
      mdd |   -.2356271   .1336453    -1.76   0.079   -.4982627   .0270084
      ind |   .3034555   .1334878     2.27   0.023   .0411295   .5657816
      cont |   .0242958   .1091984     0.22   0.824   -.1902974   .2388891
      e1 |   -.4271641   .1520123    -2.81   0.005   -.7258939   -.1284344
      e3 |   -.1283443   .2273348    -0.56   0.573   -.5750956   .3184069
      e4 |   -.4215662   .1736305    -2.43   0.016   -.7627794   -.080353
      cpi |   -.0080272   .0613787    -0.13   0.896   -.1286467   .1125923
      gdp |   -.0287721   .0180892    -1.59   0.112   -.0643205   .0067763
      blr |   .7844066   1.164292     0.67   0.501   -1.503623   3.072436
      empy |   -.6380885   .8737312    -0.73   0.466   -2.355118   1.078941
      l_ind_ndir | -.0358924   .0387096    -0.93   0.004   -.0119632   -.941784
      _cons |   3.341961   .2260059    14.79   0.000   2.897821   3.786101
-----+-----

```

```

. predict ndirH
(option xb assumed; fitted values)

```

Tests of endogeneity

Ho: variables are exogenous

```

Durbin (score) chi2(1) = 3.92117 (p = 0.0477)
Wu-Hausman F(1,456) = 3.83638 (p = 0.0508)

```

Tests of overidentifying restrictions:

Sargan (score) $\chi^2(1) = .336463$ (p = 0.5619)
 Basmann $\chi^2(1) = .326674$ (p = 0.5676)

MDD

First-stage regressions

```
. reg mdd gender ndir ind cont e1 e3 e4 cpi gdp blr empy l_dirown
```

Source	SS	df	MS	Number of obs =	470
Model	11.243574	12	.936964503	F(12, 457) =	7.10
Residual	60.2798302	457	.131903348	Prob > F =	0.0000
				R-squared =	0.1572
				Adj R-squared =	0.1351
Total	71.5234043	469	.152501928	Root MSE =	.36319

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
mdd					
gender	.0444987	.0381185	1.17	0.244	-.0304107 .1194081
ndir	-.0299586	.0162809	-1.84	0.066	-.0619533 .0020361
ind	-.2506874	.0455233	-5.51	0.000	-.3401484 -.1612264
cont	.2346075	.0366183	6.41	0.000	.1626464 .3065686
e1	.088268	.0535475	1.65	0.100	-.016962 .1934979
e3	-.0627403	.0790424	-0.79	0.428	-.2180719 .0925913
e4	.0721356	.0611484	1.18	0.239	-.0480313 .1923025
cpi	-.0277309	.0213704	-1.30	0.195	-.0697273 .0142654
gdp	-.0046856	.0063642	-0.74	0.462	-.0171923 .0078212
blr	.2575629	.4072688	0.63	0.527	-.542789 1.057915
empy	.5823639	.3049999	1.91	0.057	-.0170124 1.18174
l_dirown	.047833	.0684065	0.70	0.043	-.0865974 .1822633
_cons	.0926229	.091531	1.01	0.312	-.0872509 .2724967

```
. predict mddH
(option xb assumed; fitted values)
```

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) $\chi^2(1) = .380466$ (p = 0.5374)
 Wu-Hausman $F(1,456) = .369432$ (p = 0.5436)

Tests of overidentifying restrictions:

Sargan (score) $\chi^2(1) = .224559$ (p = 0.6356)
 Basmann $\chi^2(1) = .217974$ (p = 0.6406)

Second Stage

```
. logit status gender ind cont ndirH mddH e1 e3 e4 cpi gdp blr empy
```

Iteration 0: log likelihood = -325.77917
 Iteration 1: log likelihood = -249.70114
 Iteration 2: log likelihood = -248.67002
 Iteration 3: log likelihood = -248.66574
 Iteration 4: log likelihood = -248.66574

Logistic regression	Number of obs =	470
	LR $\chi^2(12)$ =	154.23
	Prob > χ^2 =	0.0000
Log likelihood = -248.66574	Pseudo R2 =	0.2367

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
--------	-------	-----------	---	------	----------------------

gender	.898432	.4540557	1.98	0.048	-1.788363	.9984974
ind	8.658591	1.240479	6.98	0.000	6.227298	11.08988
cont	6.013049	1.076996	5.58	0.000	1.123922	9.902176
ndirH	-3.198818	1.160285	-2.76	0.006	-5.472934	-.9247014
mdd	29.70568	4.545715	6.53	0.000	20.79625	38.61512
e1	-3.260316	.7545365	-4.32	0.000	-4.73918	-1.781452
e3	3.068766	.6242337	4.92	0.000	1.84529	4.292241
e4	-2.209931	.728017	-3.04	0.002	-3.636818	-.783044
cpi	.8440215	.1867491	4.52	0.000	.478	1.210043
gdp	.1218778	.0557371	2.19	0.029	.0126351	.2311205
blr	-3.867718	2.963842	-1.30	0.192	-9.676742	1.941306
empy	21.8911	3.549523	6.17	0.000	-28.84794	44.93407
_cons	6.565407	3.742356	1.75	0.079	-.7694756	13.90029

Model 3

NDIR

First-stage regressions

Instrumental variables (2SLS) regression

Number of obs = 470
Wald chi2(27) = 389.71
Prob > chi2 = 0.0000
R-squared = 0.3127
Root MSE = .41453

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ndir	.1764924	.1643633	1.07	0.283	-.1456537	.4986384
ebit	-.2103154	.044253	-4.75	0.000	-.2970497	-.1235812
roe	-.0383041	.016089	-2.38	0.017	-.0698378	-.0067703
tla	.138196	.0219491	6.30	0.000	.0951765	.1812156
lta	-.0295615	.1474766	-0.20	0.841	-.3186103	.2594874
cta	.0021649	.0139737	0.15	0.877	-.025223	.0295528
cle	.0236681	.0093557	2.53	0.011	.0053312	.042005
lqt	.0087038	.0348656	0.25	0.803	-.0596315	.0770391
wct	-.0145481	.038282	-0.38	0.704	-.0895795	.0604832
nwc	-3.59e-09	2.51e-09	-1.43	0.153	-8.50e-09	1.33e-09
ast	-.0003503	.000421	-0.83	0.405	-.0011753	.0004748
exp	-.0007491	.0010903	-0.69	0.492	-.002886	.0013878
logta	.0095155	.0117633	0.81	0.419	-.0135401	.0325712
logcap	.0088981	.0062088	1.43	0.152	-.0032709	.0210671
age	-.0157199	.0028247	-5.57	0.000	-.0212561	-.0101836
blc	-.067788	.0453519	-1.49	0.135	-.1566762	.0211002
gender	.2044254	.057006	3.59	0.000	.0926958	.316155
mdd	.1676254	.064943	2.58	0.010	.0403395	.2949113
ind	.0408193	.060338	0.68	0.499	-.0774411	.1590796
cont	.0671236	.0474716	1.41	0.157	-.0259189	.1601662
cpi	-.0170179	.0254774	-0.67	0.504	-.0669528	.032917
gdp	.0048374	.0080954	0.60	0.550	-.0110293	.0207041
blr	.0783931	.48416	0.16	0.871	-.8705431	1.027329
empy	-.1226184	.3643466	-0.34	0.736	-.8367245	.5914878
e1	-.0185294	.0554194	-0.33	0.738	-.1271494	.0900906
e2	-.1903881	.0835873	-2.28	0.023	-.3542163	-.02656
e3	-.1098492	.0951728	-1.15	0.248	-.2963845	.0766861
_cons	-.2697381	.4651613	-0.58	0.562	-1.181438	.6419613

Instrumented: ndir

Instruments: ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age
blc gender mdd ind cont cpi gdp blr empy e1 e2 e3 l_ind_ndir
l_tngasset

. estat endog

Tests of endogeneity

H0: variables are exogenous

Durbin (score) chi2(1) = .82627 (p = 0.2186)

Wu-Hausman F(1,441) = .96939 (p = 0.2591)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .114066 (p = 0.7356)

Basmann chi2(1) = .107053 (p = 0.7435)

MDD

Instrumental variables (2SLS) regression

Number of obs = 470
Wald chi2(27) = 675.77
Prob > chi2 = 0.0000
R-squared = 0.5796
Root MSE = .32417

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
mdd	.3557872	.9120838	0.39	0.696	-1.431864	2.143439
ebit	-.2207666	.0751788	-2.94	0.003	-.3681143	-.0734188
roe	-.0180927	.0247343	-0.73	0.464	-.066571	.0303856
tla	.1180418	.0182805	6.46	0.000	.0822126	.1538709
lta	-.1459744	.1063943	-1.37	0.170	-.3545035	.0625546
cta	.0213055	.0066358	3.21	0.001	.0082996	.0343114
cle	.0152949	.0098266	1.56	0.120	-.003965	.0345548
lqt	-.0103926	.0369405	-0.28	0.778	-.0827947	.0620095
wct	-.0111026	.037573	-0.30	0.768	-.0847444	.0625392
nwc	-2.66e-09	2.76e-09	-0.96	0.335	-8.07e-09	2.75e-09
ast	.0001538	.0002492	0.62	0.537	-.0003346	.0006422
exp	-.0000777	.0009758	-0.08	0.937	-.0019902	.0018348
logta	.0081652	.0092338	0.88	0.377	-.0099328	.0262631
logcap	.0090536	.0111295	0.81	0.416	-.0127597	.030867
age	-.011917	.0013804	-8.63	0.000	-.0146225	-.0092114
blc	-.0172484	.0799964	-0.22	0.829	-.1740385	.1395417
gender	.1332717	.0505316	2.64	0.008	.0342317	.2323118
ndir	-.0985493	.0298625	-3.30	0.001	-.1570787	-.0400198
ind	.1488625	.2556286	0.58	0.560	-.3521603	.6498853
cont	.0395504	.2105699	0.19	0.851	-.373159	.4522597
cpi	-.0008447	.0341767	-0.02	0.980	-.0678299	.0661404
gdp	.0009424	.0086862	0.11	0.914	-.0160822	.017967
blr	.2023403	.4112718	0.49	0.623	-.6037377	1.008418
empy	-.3762678	.5696679	-0.66	0.509	-1.492796	.7402608
e1	-.0479458	.0419366	-1.14	0.253	-.1301401	.0342485
e2	-.098768	.0877757	-1.13	0.260	-.2708052	.0732691
e3	-.0134251	.1248865	-0.11	0.914	-.2581981	.2313479
_cons	.4321082	.2151335	2.01	0.045	.0104543	.853762

Instrumented: mdd

Instruments: ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age
blc gender ndir ind cont cpi gdp blr empy e1 e2 e3 l_dirown
l_tngasset

. estat endog

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .080241 (p = 0.7770)

Wu-Hausman F(1,441) = .075303 (p = 0.7839)

estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .683457 (p = 0.4084)

Basmann chi2(1) = .64222 (p = 0.4229)

APPENDIX 2c: 1- year prior to bankruptcy sample endogeneity test

Model 2

NDIR

First-stage regressions

```
reg ndir gender mdd ind cont e1 e3 e4 cpi gdp blr empy l_ind_ndir
```

Source	SS	df	MS	Number of obs	=	419
Model	37.5813188	12	3.13177656	F(12, 406)	=	2.87
Residual	443.187178	406	1.09159403	Prob > F	=	0.0008
				R-squared	=	0.0782
				Adj R-squared	=	0.0509
Total	480.768496	418	1.15016387	Root MSE	=	1.0448

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	-.1494469	.1184187	-1.26	0.208	-.3822372 .0833435
mdd	-.3411453	.1295553	-2.63	0.009	-.5958283 -.0864624
ind	.2820741	.147735	1.91	0.057	-.0083469 .5724951
cont	.053707	.1107047	0.49	0.628	-.163919 .271333
e1	-.3198723	.1712836	-1.87	0.063	-.6565856 .0168411
e3	-.0791367	.252466	-0.31	0.754	-.5754404 .417167
e4	-.1528371	.1931028	-0.79	0.429	-.5324433 .226769
cpi	-.0883966	.0705629	-1.25	0.211	-.2271108 .0503177
gdp	-.0153937	.0210972	-0.73	0.466	-.0568671 .0260797
blr	-1.219778	1.135133	-1.07	0.283	-3.451249 1.011694
empy	-.9419932	.5261735	-1.79	0.074	-1.976358 .0923714
l_ind_ndir	.0114914	.0446925	0.26	0.079	-.0763663 .0993491
_cons	2.954944	.2797605	10.56	0.000	2.404984 3.504904

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 22.6102 (p = 0.0000)

Wu-Hausman F(1,404) = 23.1026 (p = 0.0000)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .009596 (p = 0.9220)

Basman chi2(1) = .009275 (p = 0.9233)

MDD

First-stage regressions

```
reg mdd ndir ind cont gender e1 e3 e4 cpi gdp blr empy l_dirown
```

Source	SS	df	MS	Number of obs	=	419
Model	14.5681776	12	1.2140148	F(12, 406)	=	7.63
Residual	64.6155933	406	.159151708	Prob > F	=	0.0000
				R-squared	=	0.1840
				Adj R-squared	=	0.1599
Total	79.1837709	418	.189434859	Root MSE	=	.39894

mdd	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ndir	-.0506439	.0187828	-2.70	0.007	-.0875677 -.0137201
ind	-.2780936	.0545156	-5.10	0.000	-.3852617 -.1709255
cont	.1317361	.0417008	3.16	0.002	.0497597 .2137125
gender	.1431841	.0445236	3.22	0.001	.0556586 .2307096
e1	.1640107	.0651938	2.52	0.012	.0358512 .2921702
e3	-.0619676	.0961187	-0.64	0.519	-.2509201 .1269848
e4	.1718477	.0732774	2.35	0.019	.0277973 .3158981

cpi		.0335811	.0269456	1.25	0.213	-.0193893	.0865515
gdp		.0184193	.0080104	2.30	0.022	.0026724	.0341663
blr		-.0850466	.4337152	-0.20	0.845	-.9376544	.7675612
empy		.0661627	.2016111	0.33	0.743	-.3301693	.4624947
l_dirown		-.1350791	.1063177	-1.27	0.035	-.344081	.0739228
_cons		.193564	.1044175	1.85	0.065	-.0117025	.3988304

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 4.62424 (p = 0.0315)
Wu-Hausman F(1,404) = 4.51936 (p = 0.0341)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .322446 (p = 0.5701)
Basmann chi2(1) = .311887 (p = 0.5765)

Second Stage

logit status gender mddHat ndirHat cont ind e1 e3 e4 cpi gdp blr empy

Iteration 0: log likelihood = -290.42748
Iteration 1: log likelihood = -208.92727
Iteration 2: log likelihood = -208.20109
Iteration 3: log likelihood = -208.19835
Iteration 4: log likelihood = -208.19835

Logistic regression
Log likelihood = -208.19835
Number of obs = 419
LR chi2(12) = 164.46
Prob > chi2 = 0.0000
Pseudo R2 = 0.2831

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender		1.54892	.4927134	3.09	0.002	-2.490595 .591945
mddHat		14.2757	2.665267	5.36	0.000	9.051871 19.49953
ndirHat		-4.481904	.9152563	-4.90	0.000	-6.275773 -2.688034
cont		.884957	.4149108	1.97	0.049	-1.631706 .052854
ind		5.76669	.8969751	6.43	0.000	4.008651 7.524729
e1		-2.998559	.6923674	-4.33	0.000	-4.355574 -1.641543
e3		2.055155	.6085155	3.38	0.001	.8624863 3.247823
e4		-1.698174	.6529996	-2.60	0.009	-2.97803 -.4183186
cpi		.5750639	.2085858	2.76	0.006	.9838846 2.166432
gdp		.2138784	.0760038	2.81	0.005	-.3628431 .67649136
blr		-1.099293	2.923527	-0.38	0.707	-6.829301 4.630714
empy		-.998131	1.544966	-0.65	0.518	-4.026209 2.029946
_cons		10.79019	2.762796	3.91	0.000	5.375207 16.20517

Model 3

NDIR

First-stage regressions

reg ndir ebit roe tla lta cta cle lgt wct nwc ast exp logta logcap age blc gender mdd
ind cont e1 e3 e4 cont cpi gdp blr empy l_ind_ndir
note: cont omitted because of collinearity

Source		SS	df	MS	Number of obs =	419
Model		80.026226	27	2.9639343	F(27, 391) =	2.89
Residual		400.74227	391	1.02491629	Prob > F =	0.0000
Total		480.768496	418	1.15016387	R-squared =	0.1665
					Adj R-squared =	0.1089
					Root MSE =	1.0124

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ebit	.1410147	.1200681	1.17	0.241	-.0950452	.3770745
roe	.0361513	.0236007	1.53	0.126	-.010249	.0825515
tla	-.1052028	.0818028	-1.29	0.199	-.2660312	.0556257
lta	.033969	.180499	0.19	0.851	-.3209009	.3888389
cta	-.0310053	.1285867	-0.24	0.810	-.2838132	.2218026
cle	.0007835	.032696	0.02	0.981	-.0634985	.0650655
lqt	.0532845	.0553212	0.96	0.336	-.0554796	.1620486
wct	-.1210154	.0671675	-1.80	0.072	-.2530701	.0110392
nwc	7.83e-09	8.85e-09	0.88	0.377	-9.57e-09	2.52e-08
ast	.1878657	.0491634	3.82	0.000	.0912081	.2845233
exp	-.1715328	.1344195	-1.28	0.203	-.4358083	.0927426
logta	-.0277264	.0270413	-1.03	0.306	-.080891	.0254381
logcap	.0373969	.0172489	2.17	0.031	.0034846	.0713092
age	.0039483	.0045015	0.88	0.381	-.0049019	.0127985
blc	.0580656	.1082793	0.54	0.592	-.1548169	.2709481
gender	-.0232329	.1188027	-0.20	0.845	-.2568049	.2103392
mdd	-.275184	.1283586	-2.14	0.033	-.5275433	-.0228246
ind	.3366202	.1509548	2.23	0.026	.0398356	.6334048
cont	.085477	.1091395	0.78	0.434	-.1290967	.3000506
e1	-.2369829	.1717266	-1.38	0.168	-.5746059	.1006401
e3	.0033629	.2535117	0.01	0.989	-.4950536	.5017794
e4	-.0351725	.1934925	-0.18	0.856	-.4155884	.3452433
cpi	-.1021356	.0694706	-1.47	0.142	-.2387182	.034447
gdp	-.0144549	.0210808	-0.69	0.493	-.0559007	.0269909
blr	-.825564	1.126653	-0.73	0.464	-3.040619	1.389491
empy	-.4921144	.5244287	-0.94	0.349	-1.523167	.5389384
l_ind_ndir	-.0190209	.0443504	-0.43	0.038	-.106216	.0681741
_cons	2.737516	.4906063	5.58	0.000	1.77296	3.702072

```
. predict ndirHat , xb
(1 missing value generated)
```

```
. estat endog
```

Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(1) = 17.6442 (p = 0.0000)
Wu-Hausman F(1,389) = 17.1438 (p = 0.0000)

```
. estat overid
```

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .002841 (p = 0.9575)
Basmann chi2(1) = .002644 (p = 0.9590)

```
. estat endog
```

MDD

First-stage regressions

```
. reg mdd ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age blc gender
ndir ind cont e1 e3 e4 cpi gdp blr empy l_dirown
```

Source	SS	df	MS	Number of obs =	419
Model	17.2834986	27	.640129576	F(27, 391) =	4.04
Residual	61.9002723	391	.158312717	Prob > F =	0.0000
				R-squared =	0.2183
				Adj R-squared =	0.1643
Total	79.1837709	418	.189434859	Root MSE =	.39789

mdd	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ebit	.0018855	.0472092	0.04	0.968	-.0909302	.0947012
roe	-.0009714	.0092769	-0.10	0.917	-.0192102	.0172674

```

      tla | .0155322 .032181 0.48 0.630 -.0477372 .0788016
      lta | -.0248031 .071053 -0.35 0.727 -.1644969 .1148906
      cta | -.023126 .0507995 -0.46 0.649 -.1230005 .0767484
      cle | .0160224 .0128233 1.25 0.212 -.0091889 .0412337
      lqt | -.0191329 .0217348 -0.88 0.379 -.0618646 .0235988
      wct | .0361784 .0264423 1.37 0.172 -.0158084 .0881653
      nwc | 1.62e-09 3.48e-09 0.47 0.642 -5.22e-09 8.46e-09
      ast | -.0249896 .0196377 -1.27 0.204 -.0635983 .0136191
      exp | -.0649386 .0526159 -1.23 0.218 -.168384 .0385069
      logta | -.0099019 .0106126 -0.93 0.351 -.0307668 .010963
      logcap | -.008362 .006804 1.23 0.220 -.005015 .0217389
      age | -.0007692 .0017706 -0.43 0.664 -.0042504 .002712
      blc | -.0130278 .0425632 -0.31 0.760 -.0967092 .0706535
      gender | .1175554 .0461661 2.55 0.011 .0267905 .2083203
      ndir | -.0423842 .019765 -2.14 0.033 -.0812432 -.0035252
      ind | -.2810546 .0577851 -4.86 0.000 -.3946629 -.1674463
      cont | .1187024 .0424769 2.79 0.005 .0351907 .2022141
      e1 | .1577799 .0671992 2.35 0.019 .025663 .2898969
      e3 | -.0779701 .0993377 -0.78 0.433 -.273273 .1173328
      e4 | .17047 .0755355 2.26 0.025 .0219635 .3189765
      cpi | .0326263 .027329 1.19 0.233 -.0211039 .0863565
      gdp | .0152897 .0082504 1.85 0.065 -.0009309 .0315104
      blr | -.1323407 .442271 -0.30 0.765 -1.001867 .7371861
      empty | .047295 .206208 0.23 0.819 -.3581203 .4527102
      l_dirown | -.1308298 .1081021 -1.21 0.001 -.3433638 -.081042
      _cons | .3735038 .1903498 1.96 0.050 -.0007334 .7477409
-----

```

```

. predict mddHat
(option xb assumed; fitted values)
(1 missing value generated)

```

```

Tests of endogeneity
Ho: variables are exogenous

```

```

Durbin (score) chi2(1) = 2.76962 (p = 0.08903)
Wu-Hausman F(1,389) = 2.71755 (p = 0.08097)

```

```

. estat overid

```

```

Tests of overidentifying restrictions:

```

```

Sargan (score) chi2(1) = .741451 (p = 0.3892)
Basmann chi2(1) = .691236 (p = 0.4057)

```

Second stage

```

. logit status ebit roe tla lta cta cle lqt wct nwc ast exp logta logcap age blc
gender ndirHat mddHat ind cont e1 e3 e4 cpi gdp blr empty

```

```

Iteration 0: log likelihood = -290.42748
Iteration 1: log likelihood = -103.42471
Iteration 2: log likelihood = -90.227464
Iteration 3: log likelihood = -88.388842
Iteration 4: log likelihood = -88.381547
Iteration 5: log likelihood = -88.381547

```

```

Logistic regression                                Number of obs   =      419
                                                    LR chi2(27)    =     404.09
                                                    Prob > chi2     =     0.0000
Log likelihood = -88.381547                      Pseudo R2      =     0.6957

```

```

-----+-----
      status |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      ebit |   .4622178   .5077928     0.91   0.363   - .5330377   1.457473
      roe |  -.2405449   .1387364    -1.73   0.083   - .5124632   .0313734
      tla |   .3036579   .4756603     0.64   0.023   - .6286191   1.235935
      lta |   .200271   .7292782     0.27   0.784   -1.229088   1.62963
      cta |   .6919346   .6278077     1.10   0.270   - .5385459   1.922415
      cle |   .0741327   .1545613     0.48   0.631   - .2288019   .3770674
      lqt |  -.5254507   .2784484    -1.89   0.059   -1.0712     .0202982
      wct |  -.2920542   .3688501    -0.79   0.428   -1.014987   .4308787

```

nwc		-2.36e-08	3.66e-08	-0.64	0.519	-9.54e-08	4.82e-08
ast		-1.018908	.5418858	-1.88	0.060	-2.080984	.043169
exp		-1.126935	.6848204	-1.65	0.100	-2.469159	.215288
logta		.1089366	.1393684	0.78	0.434	-.1642205	.3820937
logcap		.1565173	.1261968	1.24	0.215	-.0908239	.4038584
age		-.090632	.0238068	-3.81	0.000	-.1372926	-.0439715
blc		-.4910855	.504107	-0.97	0.030	-1.479117	.4969459
gender		-.6295123	.6803399	-0.93	0.355	-1.962954	.7039295
ndirHat		-6.574097	1.999179	-3.29	0.001	-10.49242	-2.655779
mddHat		13.97943	4.801198	2.91	0.004	4.569257	23.38961
ind		6.321943	1.721564	3.67	0.000	2.94774	9.696146
cont		.1715148	.737244	0.23	0.016	1.616487	1.273457
e1		-2.561488	1.19005	-2.15	0.031	-4.893943	-.2290325
e3		3.973091	1.131032	3.51	0.000	1.756308	6.189873
e4		-.0901203	1.128068	-0.08	0.936	-2.301093	2.120852
cpi		-.825382	.3784602	-2.18	0.029	-1.56715	-.0836136
gdp		-.177437	.1183364	-1.50	0.134	-.4093722	.0544982
blr		-7.824671	5.107602	-1.53	0.126	-17.83539	2.186045
empy		3.55441	2.408337	1.47	0.010	-8.270695	1.169812
_cons		14.63927	5.86652	2.50	0.013	3.141104	26.13744

Note: 3 failures and 0 successes completely determined.

APPENDIX 3: Artificial Neural Network for Malaysia Sample

APPENDIX 3a: Model 1 (3-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	68.921
	Percent Incorrect Predictions	17.1%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
Holdout	Training Time	0:00:00.07
	Percent Incorrect Predictions	23.9%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted	
		Hidden Layer 1	Output Layer
		H(1:1)	[STATUS=0] [STATUS=1]
Input Layer	(Bias)	-.491	
	EBIT	-.150	
	ROE	.936	
	TLA	-2.438	
	LTA	.298	
	CTA	.058	
	CLE	-.174	
	LQT	1.006	
	WCT	-.328	
	NWC	1.196	
	AST	.083	
	EXP	-.769	
	LogTA	-.034	
	LogCAP	-.501	
	AGE	3.434	
	BLC	.238	
Hidden Layer 1	(Bias)		-1.844 1.846
	H(1:1)		4.652 -4.652

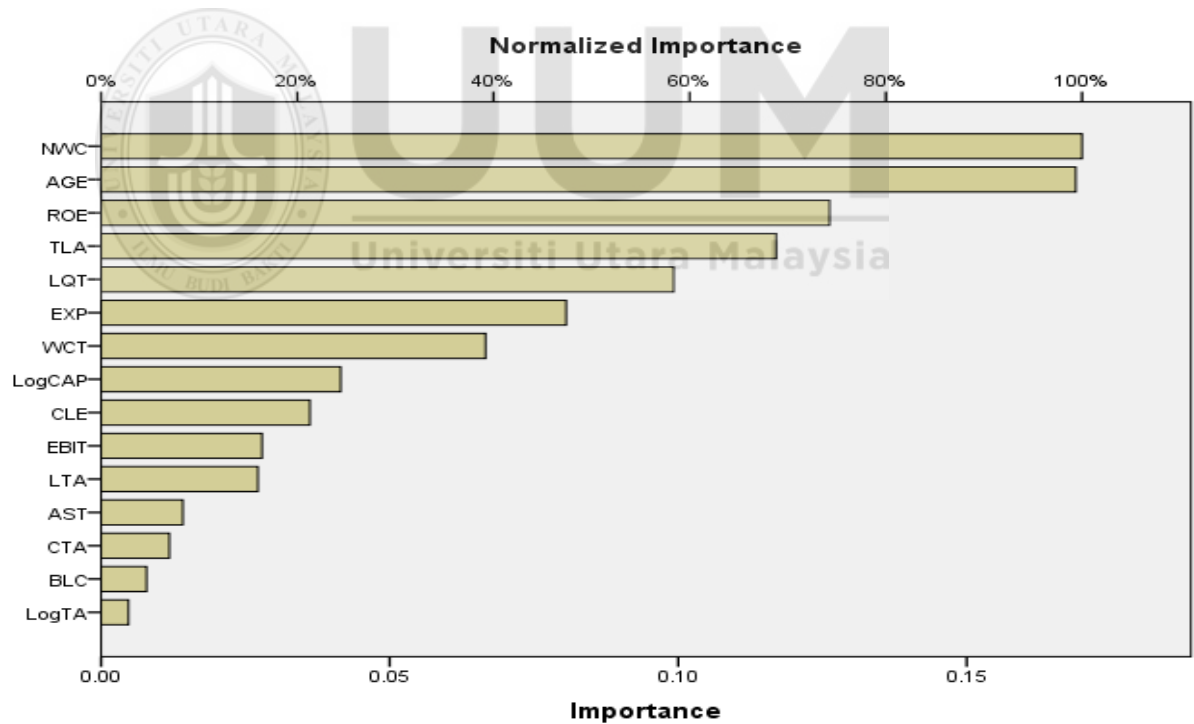
Classification

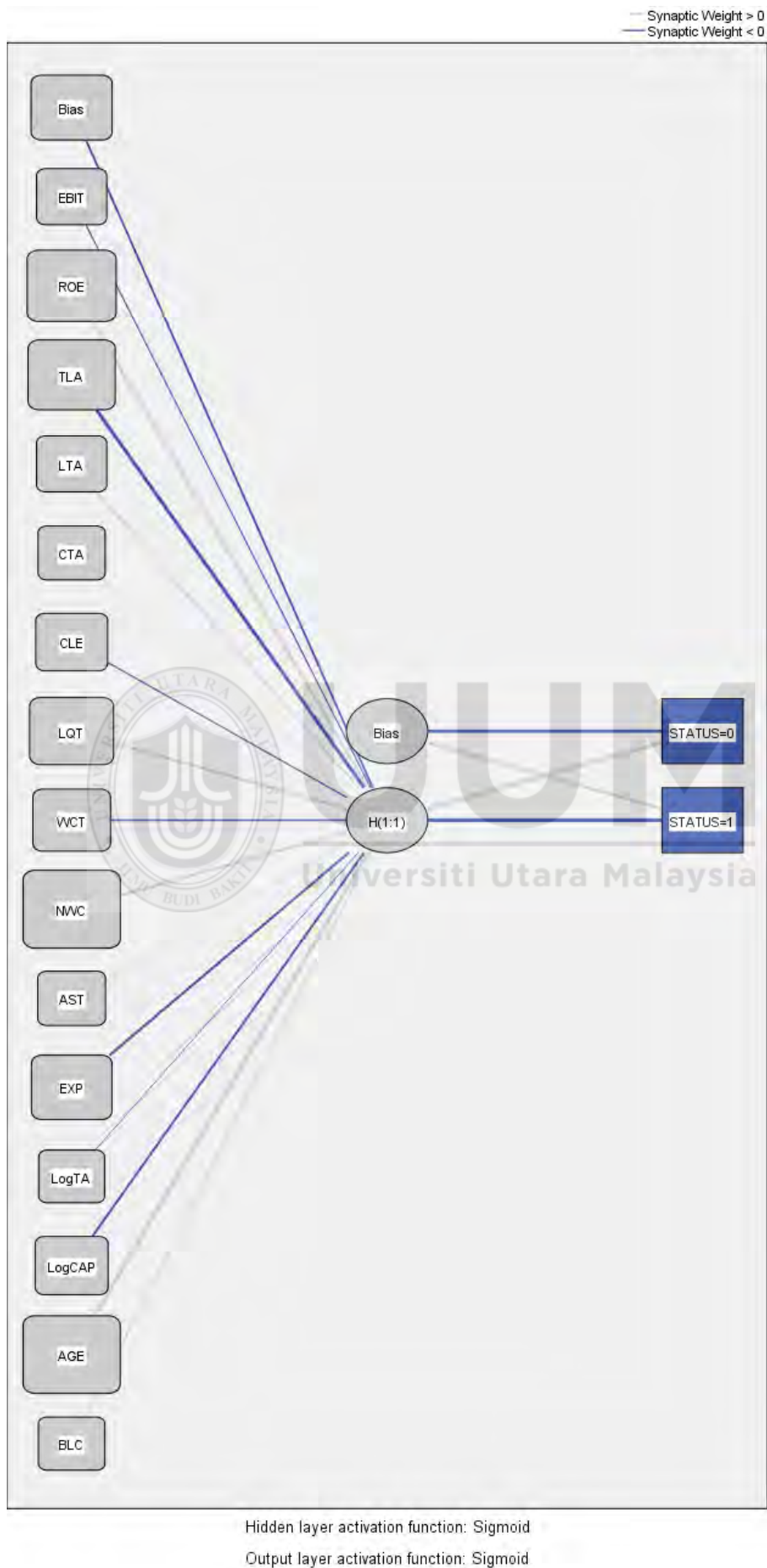
Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	211	56	79.0%
	Failed	35	230	86.8%
	Overall Percent	46.2%	53.8%	82.9%
	Non-Failed	49	17	74.2%
Holdout	Failed	15	53	77.9%
	Overall Percent	47.8%	52.2%	76.1%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
EBIT	.028	16.4%
ROE	.126	74.3%
TLA	.117	68.8%
LTA	.027	16.0%
CTA	.012	7.0%
CLE	.036	21.3%
LQT	.099	58.4%
WCT	.067	39.2%
NWC	.170	100.0%
AST	.014	8.3%
EXP	.081	47.4%
LogTA	.005	2.8%
LogCAP	.042	24.4%
AGE	.169	99.4%
BLC	.008	4.6%





APPENDIX 3b: Model 2 (3-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	97.222
	Percent Incorrect Predictions	25.2%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.12
Holdout	Percent Incorrect Predictions	26.4%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-3.588		
	GENDER	-4.587		
	MDD	-6.483		
	NDIR	8.133		
	IND	-.805		
	CONT	-4.173		
	CINA	-1.209		
	INDIAN	-3.630		
	MELAYU	-4.867		
	CPI	-.307		
	GDP	-1.016		
	BLR	1.097		
	EMPY	-.577		
	(Bias)		-1.074	1.060
Hidden Layer 1	H(1:1)		2.627	-2.635

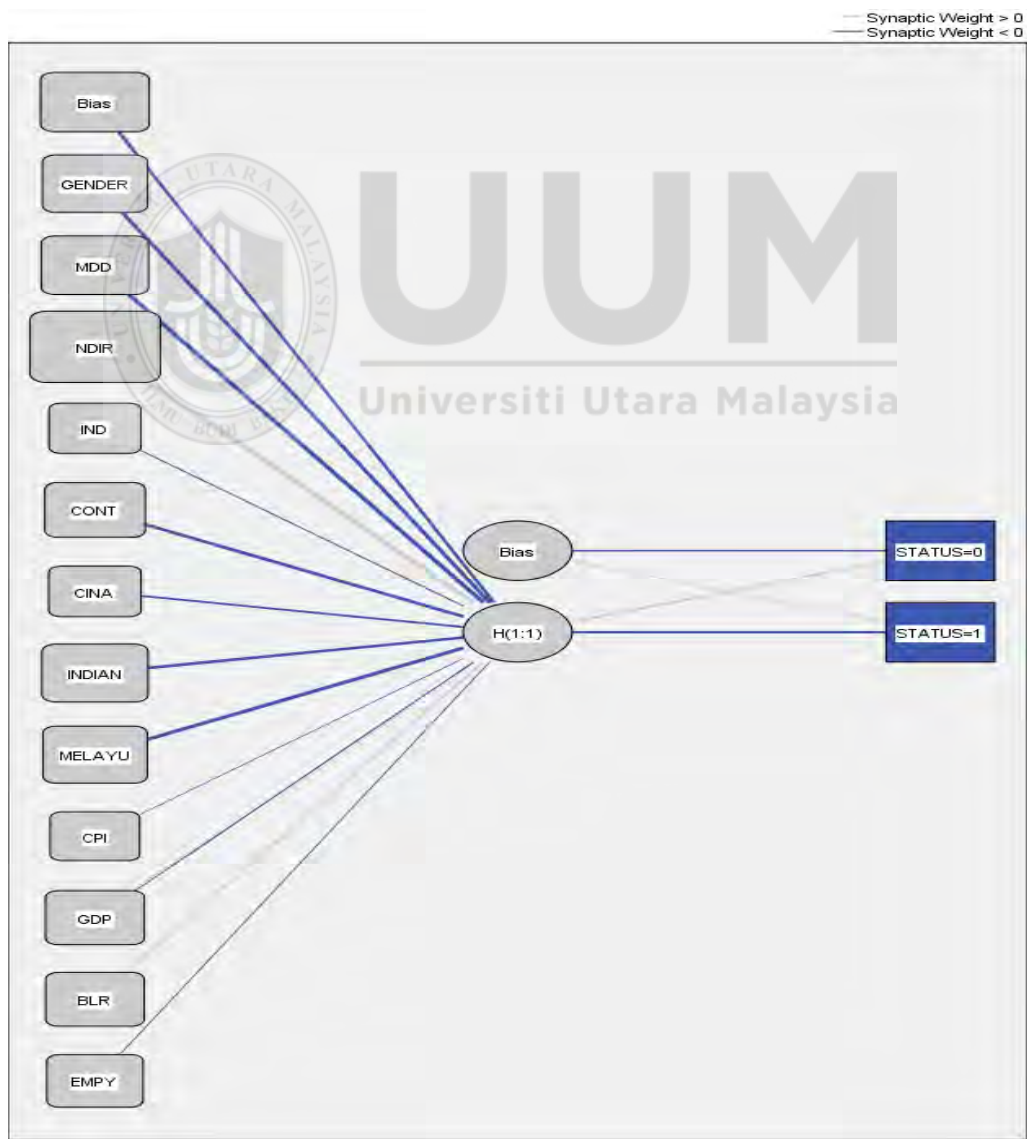
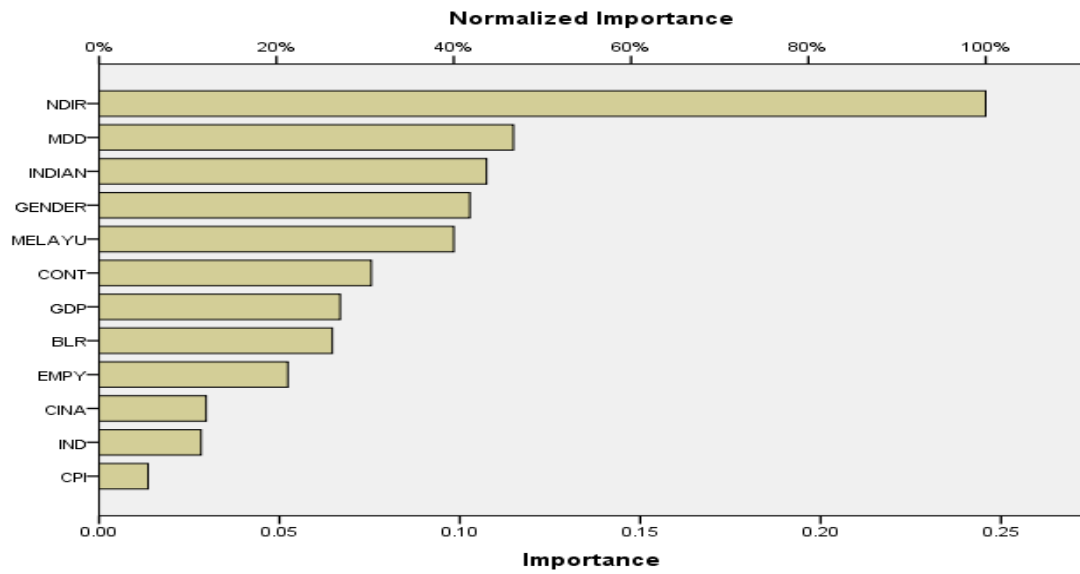
Classification

Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	176	82	68.2%
	Failed	51	218	81.0%
	Overall Percent	43.1%	56.9%	74.8%
Holdout	Non-Failed	46	23	66.7%
	Failed	11	49	81.7%
	Overall Percent	44.2%	55.8%	73.6%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.103	41.8%
MDD	.115	46.7%
NDIR	.246	100.0%
IND	.028	11.5%
CONT	.075	30.7%
CINA	.030	12.1%
INDIAN	.107	43.7%
MELAYU	.098	40.0%
CPI	.014	5.5%
GDP	.067	27.2%
BLR	.065	26.3%
EMPY	.052	21.3%



Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

APPENDIX 3c: Model 3 (3-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	49.904
	Percent Incorrect Predictions	10.3%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
Holdout	Training Time	0:00:00.17
	Percent Incorrect Predictions	16.5%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-.877		
	GENDER	-3.916		
	MDD	-1.854		
	NDIR	3.179		
	IND	-1.540		
	CONT	-.093		
	CINA	-4.243		
	INDIAN	-4.241		
	MELAYU	-4.168		
	CPI	2.260		
	GDP	1.000		
	BLR	-2.097		
	EMPY	-1.630		
	EBIT	.040		
	ROE	2.311		
	TLA	-5.809		
	LTA	-.522		
	CTA	1.022		
	CLE	-1.391		
	LQT	2.167		
	WCT	-1.315		
	NWC	2.172		
	AST	1.500		
	EXP	.938		
	LogTA	-3.203		
	LogCAP	.468		
	AGE	13.024		
	BLC	2.423		
Hidden Layer 1	(Bias)		-2.012	2.015
	H(1:1)		5.410	-5.368

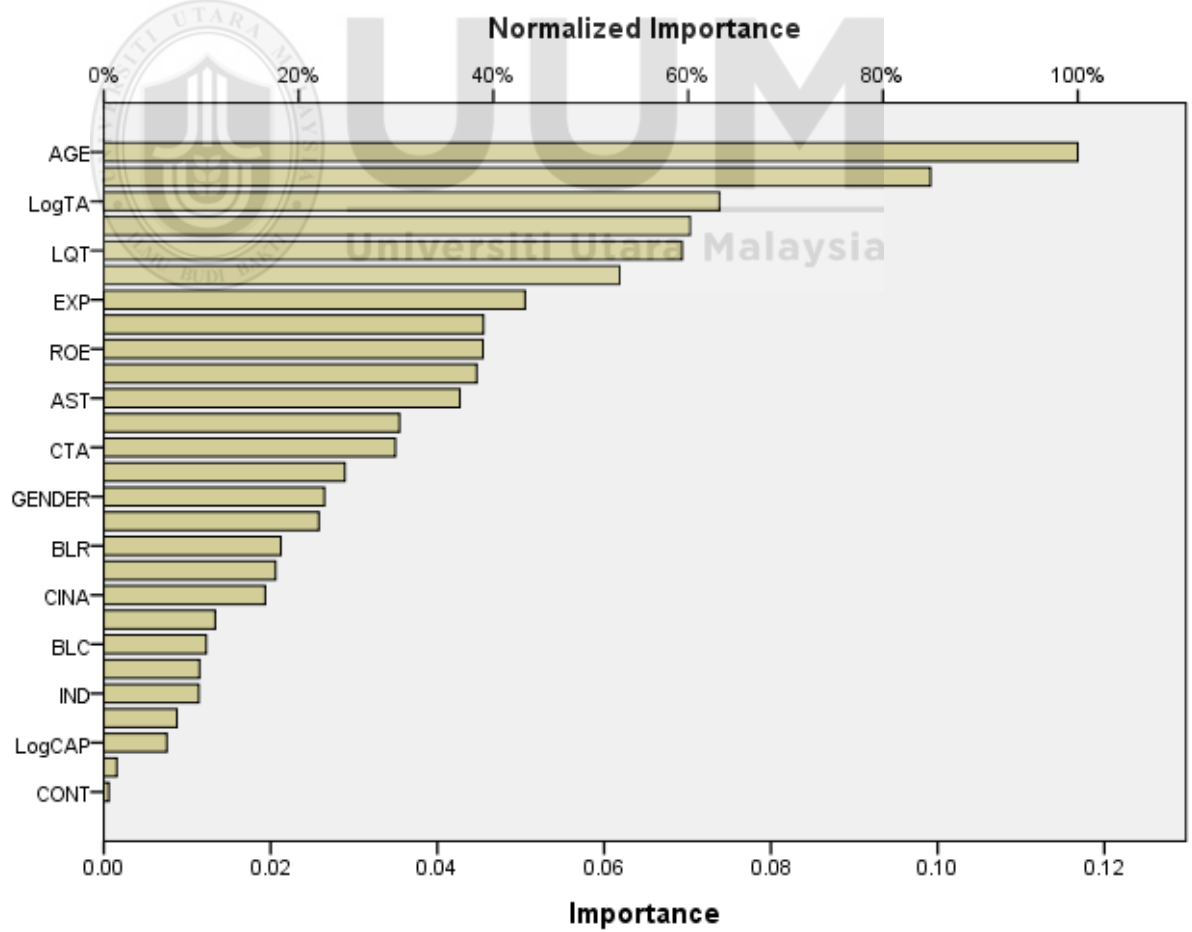
Classification

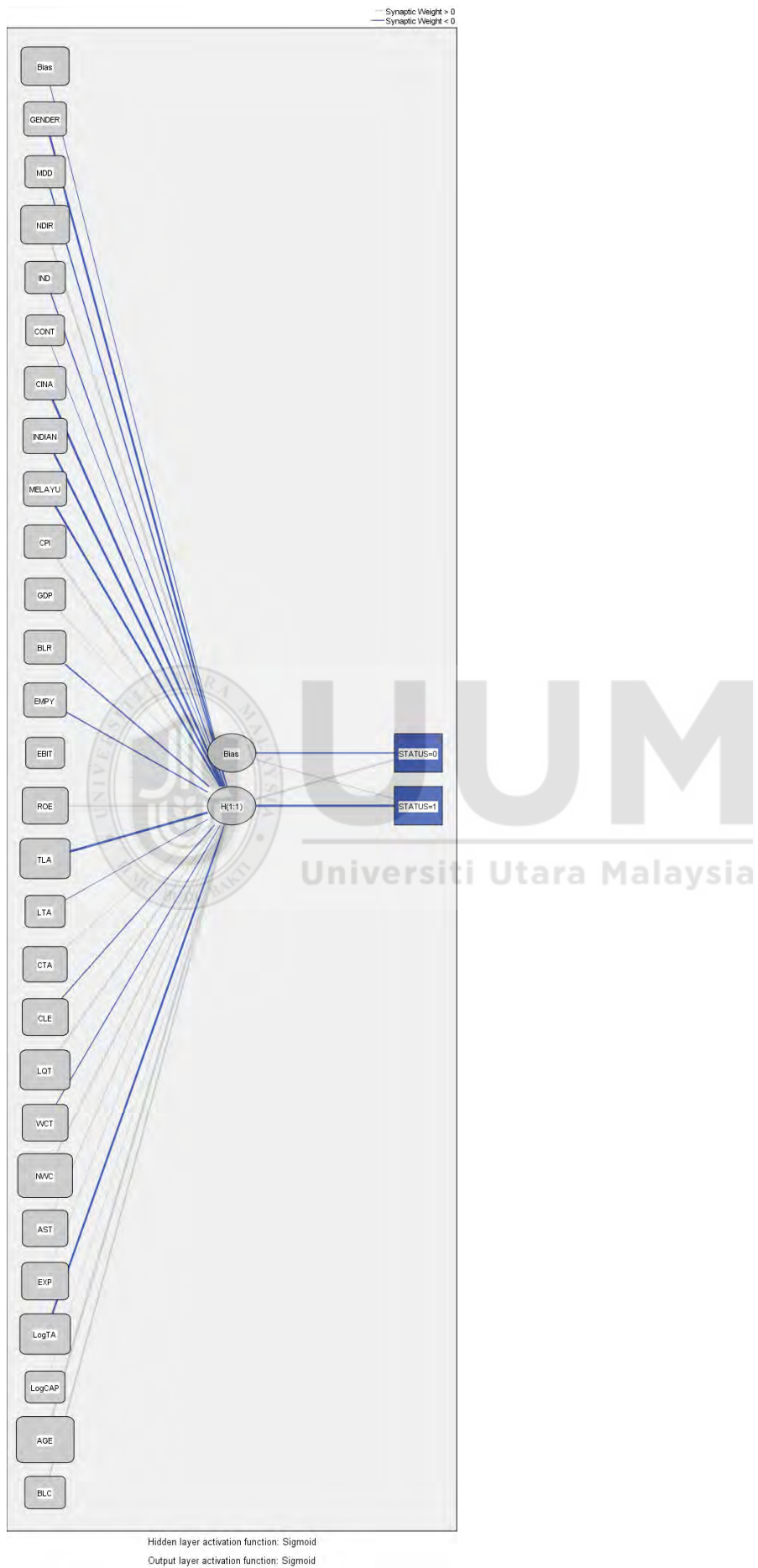
Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	220	37	85.6%
	Failed	17	249	93.6%
	Overall Percent	45.3%	54.7%	89.7%
	Non-Failed	57	13	81.4%
Holdout	Failed	9	54	85.7%
	Overall Percent	49.6%	50.4%	83.5%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.026	22.6%
MDD	.011	9.8%
NDIR	.062	53.0%
IND	.011	9.7%
CONT	.001	0.5%
CINA	.019	16.6%
INDIAN	.035	30.3%
MELAYU	.029	24.8%
CPI	.021	17.6%
GDP	.013	11.4%
BLR	.021	18.2%
EMPY	.026	22.1%
EBIT	.002	1.3%
ROE	.045	38.9%
TLA	.070	60.2%
LTA	.009	7.5%
CTA	.035	29.9%
CLE	.046	39.0%
LQT	.069	59.4%
WCT	.045	38.3%
NWC	.099	84.9%
AST	.043	36.5%
EXP	.051	43.2%
LogTA	.074	63.2%
LogCAP	.008	6.5%
AGE	.117	100.0%
BLC	.012	10.5%





APPENDIX 3d: Model 1 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	23.609
	Percent Incorrect Predictions	7.7%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.11
Holdout	Percent Incorrect Predictions	9.3%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-2.164		
	EBIT	6.543		
	ROE	-.864		
	TLA	-3.670		
	LTA	.521		
	CTA	-2.974		
	CLE	-.971		
	LQT	.845		
	WCT	-.588		
	NWC	.027		
	AST	.286		
	EXP	1.067		
	LogTA	-.456		
	LogCAP	-.373		
	AGE	1.942		
	BLC	-.228		
Hidden Layer 1	(Bias)		-3.383	3.383
	H(1:1)		6.972	-6.973

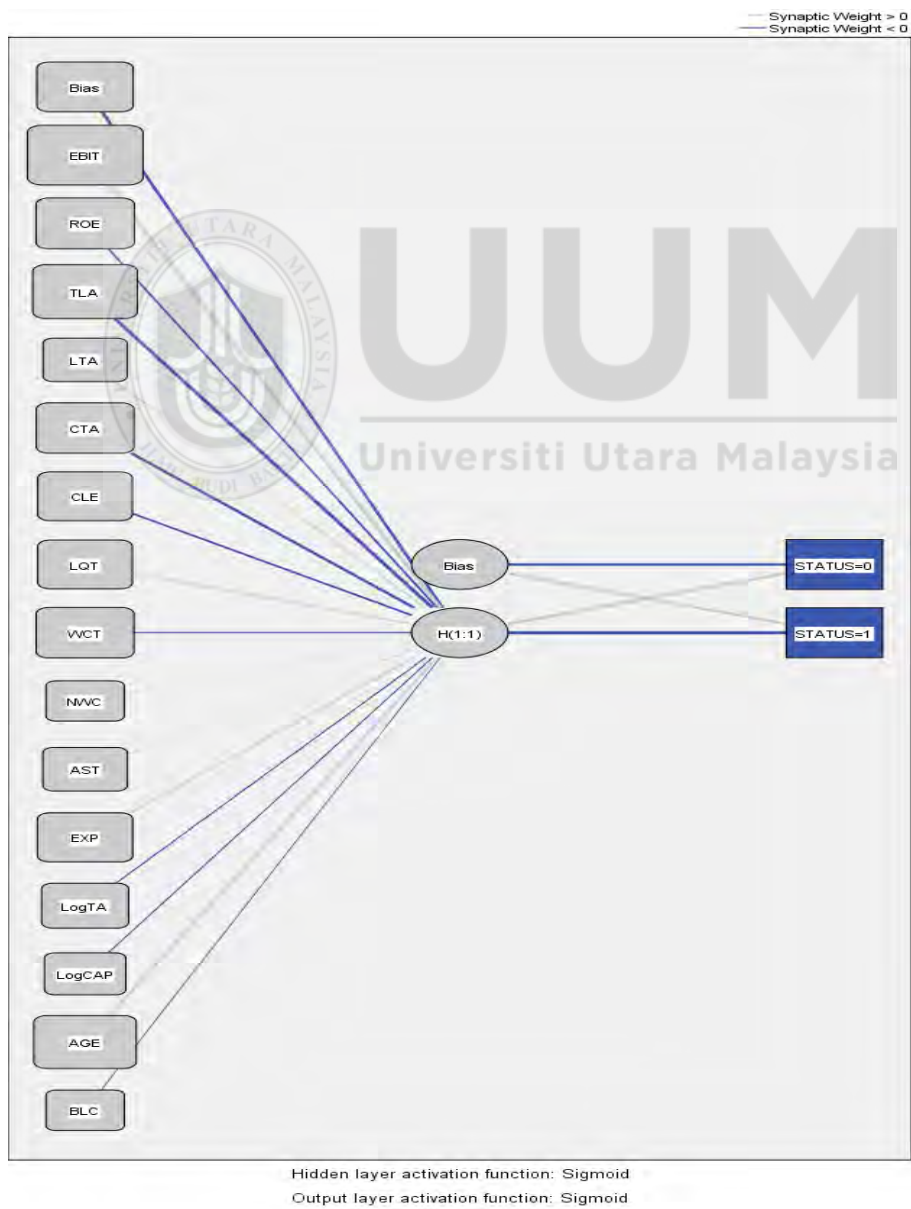
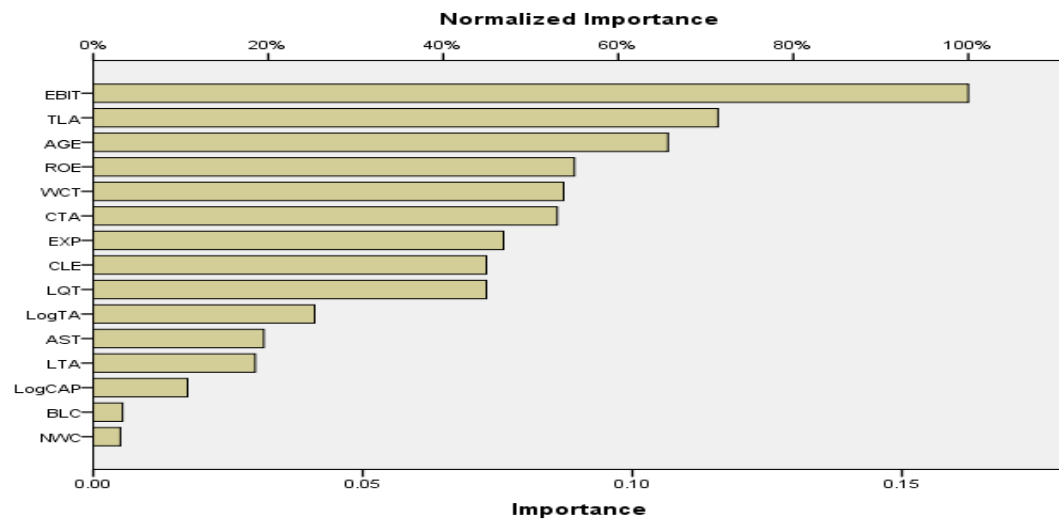
Classification

Sample	Observed	Predicted		
		Non-failed	Failed	Percent Correct
Training	Non-failed	157	18	89.7%
	Failed	10	177	94.7%
	Overall Percent	46.1%	53.9%	92.3%
Holdout	Non-failed	53	7	88.3%
	Failed	3	45	93.8%
	Overall Percent	51.9%	48.1%	90.7%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
EBIT	.162	100.0%
ROE	.089	55.0%
TLA	.116	71.4%
LTA	.030	18.5%
CTA	.086	53.0%
CLE	.073	44.9%
LQT	.073	44.9%
WCT	.087	53.8%
NWC	.005	3.1%
AST	.032	19.5%
EXP	.076	46.9%
LogTA	.041	25.3%
LogCAP	.018	10.8%
AGE	.107	65.7%
BLC	.005	3.3%



APPENDIX 3e: Model 2 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	56.282
	Percent Incorrect Predictions	20.5%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.07
Holdout	Percent Incorrect Predictions	26.7%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	.426		
	GENDER	-1.617		
	MDD	-.535		
	NDIR	3.418		
	IND	-.493		
	CONT	-1.162		
	CINA	-.871		
	INDIAN	-1.423		
	MELAYU	-1.408		
	CPI	-.629		
	GDP	-.763		
	BLR	-.380		
	EMPY	.196		
Hidden Layer 1	(Bias)		-1.890	1.891
	H(1:1)		3.737	-3.736

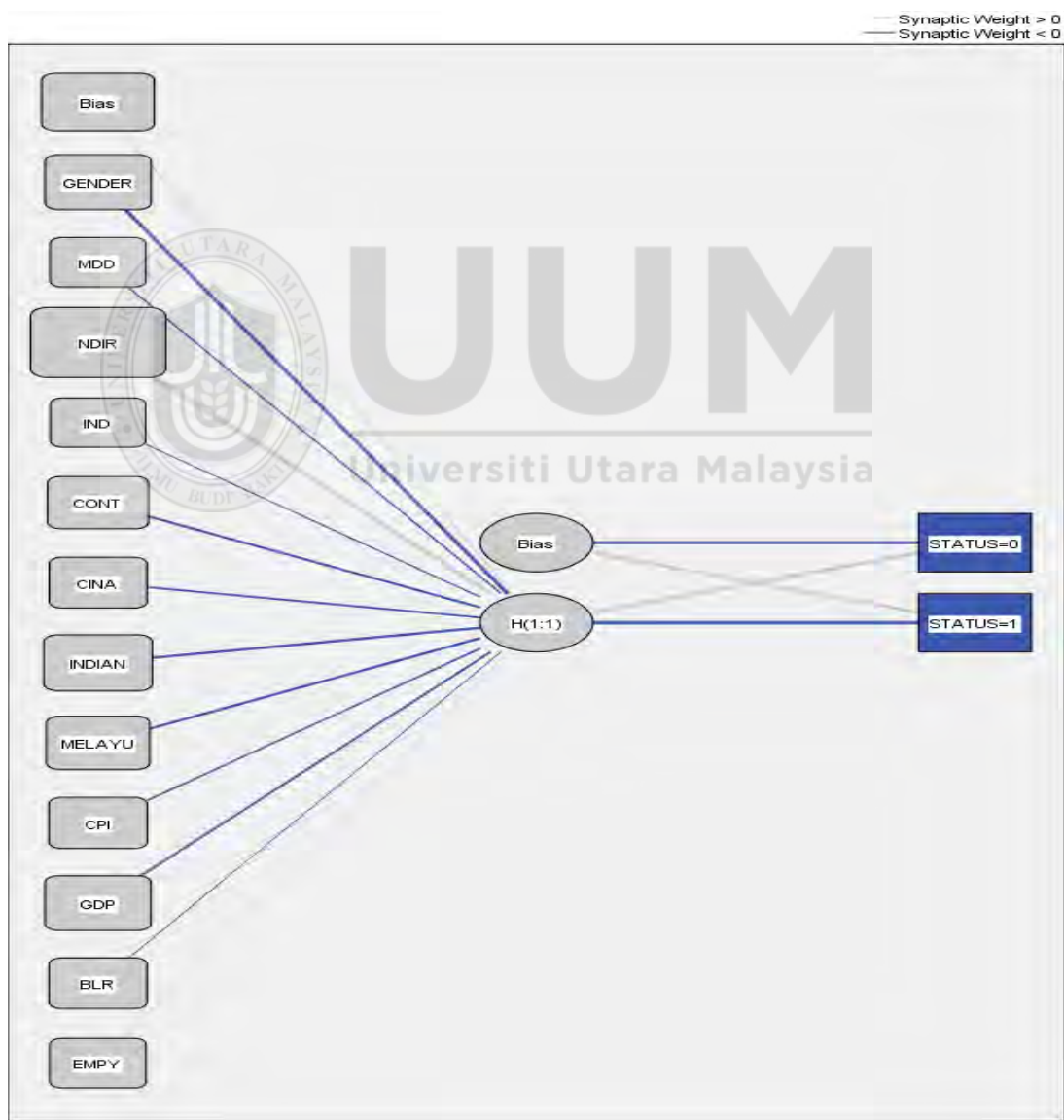
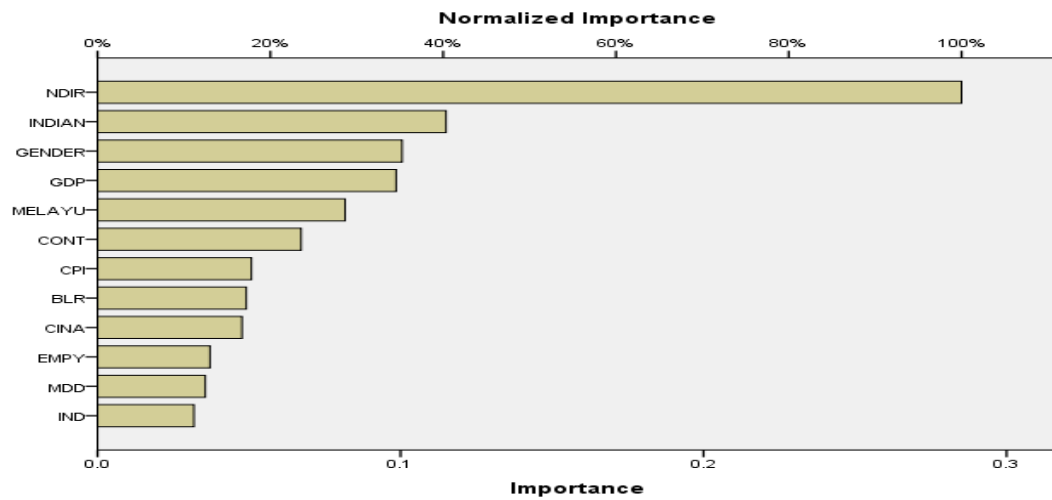
Classification

Sample	Observed	Predicted		
		Non-failed	Failed	Percent Correct
Training	Non-failed	139	40	77.7%
	Failed	35	151	81.2%
	Overall Percent	47.7%	52.3%	79.5%
Holdout	Non-failed	40	16	71.4%
	Failed	12	37	75.5%
	Overall Percent	49.5%	50.5%	73.3%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.100	35.2%
MDD	.036	12.5%
NDIR	.285	100.0%
IND	.032	11.2%
CONT	.067	23.6%
CINA	.048	16.7%
INDIAN	.115	40.3%
MELAYU	.082	28.6%
CPI	.051	17.8%
GDP	.099	34.5%
BLR	.049	17.2%
EMPY	.037	13.0%



APPENDIX 3f: Model 3 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	10.773
	Percent Incorrect Predictions	2.4%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
	Training Time	0:00:00.09
Holdout	Percent Incorrect Predictions	8.9%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	1.587		
	GENDER	.313		
	MDD	1.152		
	NDIR	-2.550		
	IND	.932		
	CONT	.587		
	CINA	-.695		
	INDIAN	.018		
	MELAYU	.018		
	CPI	-.765		
	GDP	-.027		
	BLR	.671		
	EMPY	-.962		
	EBIT	-6.891		
	ROE	-1.264		
	TLA	8.900		
	LTA	-.633		
	CTA	3.140		
	CLE	.213		
	LQT	-2.571		
	WCT	1.859		
	NWC	-.780		
	AST	.629		
	EXP	.724		
	LogTA	1.335		
	LogCAP	.665		
	AGE	-5.080		
	BLC	.317		
Hidden Layer 1	(Bias)		4.284	-4.306
	H(1:1)		-10.210	10.203

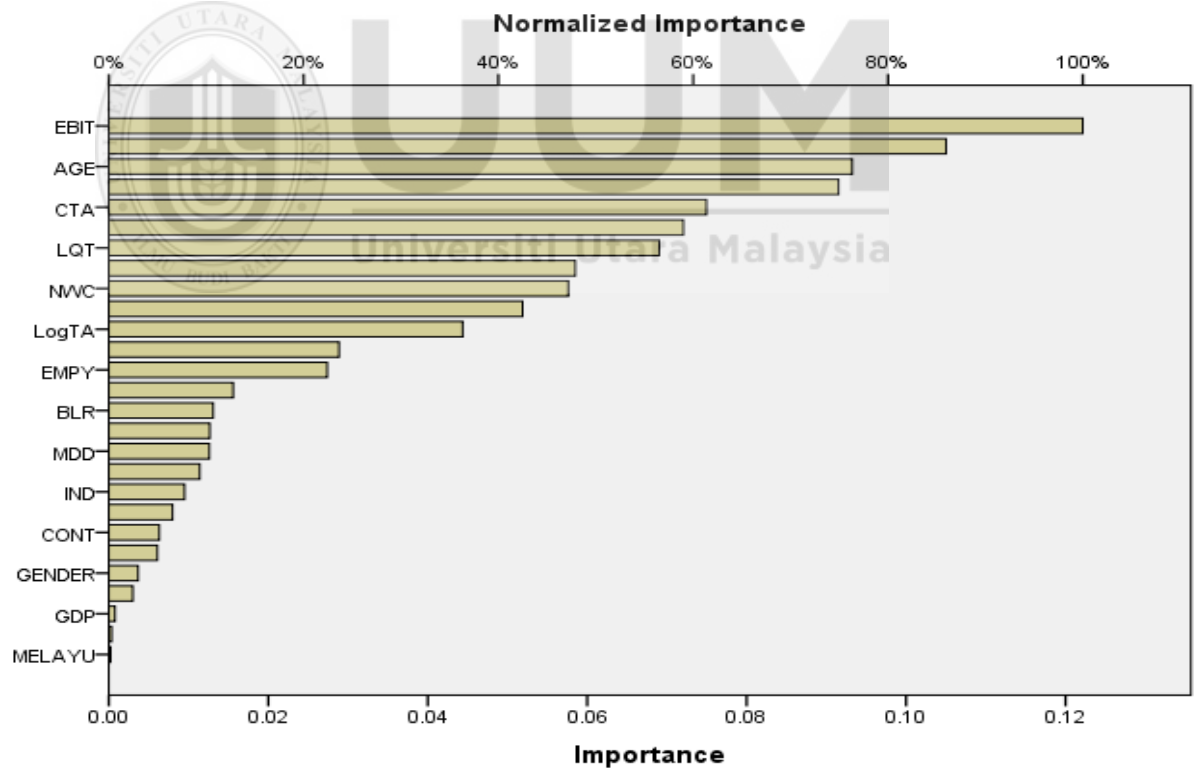
Classification

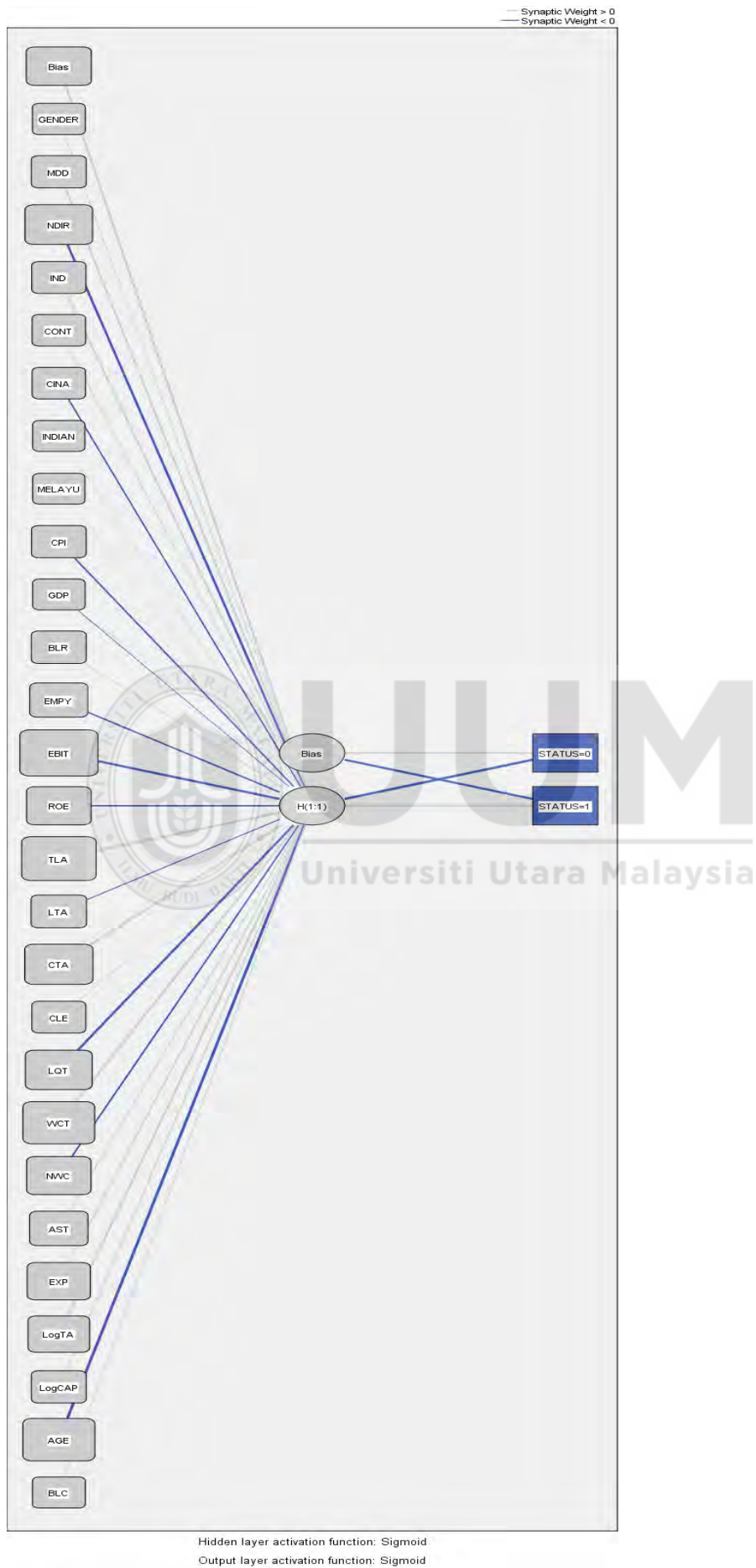
Sample	Observed	Predicted		
		Non-failed	Failed	Percent Correct
Training	Non-failed	178	3	98.3%
	Failed	6	182	96.8%
	Overall Percent	49.9%	50.1%	97.6%
	Non-failed	50	4	92.6%
Holdout	Failed	5	42	89.4%
	Overall Percent	54.5%	45.5%	91.1%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.004	3.0%
MDD	.013	10.3%
NDIR	.072	59.0%
IND	.009	7.8%
CONT	.006	5.2%
CINA	.006	5.0%
INDIAN	.000	0.3%
MELAYU	.000	0.2%
CPI	.011	9.3%
GDP	.001	0.6%
BLR	.013	10.7%
EMPY	.027	22.4%
EBIT	.122	100.0%
ROE	.059	47.9%
TLA	.105	86.0%
LTA	.016	12.8%
CTA	.075	61.3%
CLE	.008	6.5%
LQT	.069	56.5%
WCT	.092	74.9%
NWC	.058	47.2%
AST	.029	23.6%
EXP	.052	42.5%
LogTA	.044	36.3%
LogCAP	.013	10.4%
AGE	.093	76.3%
BLC	.003	2.5%





APPENDIX 3g: Model 1 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	25.346
	Percent Incorrect Predictions	8.1%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
	Training Time	0:00:00.10
Holdout	Percent Incorrect Predictions	11.8%

Dependent Variable: STATUS

Parameter Estimates

Predictor	Predicted		
	Hidden Layer 1	Output Layer	
	H(1:1)	[STATUS=0]	[STATUS=1]
(Bias)	-5.059		
EBIT	-1.415		
ROE	-9.064		
TLA	1.617		
LTA	.543		
CTA	2.172		
CLE	1.017		
LQT	-7.747		
WCT	.842		
NWC	2.160		
AST	-17.394		
EXP	-2.967		
LogTA	2.735		
LogCAP	.574		
AGE	-5.788		
BLC	-2.331		
Hidden Layer 1	(Bias)	3.111	-3.115
	H(1:1)	-5.560	5.557

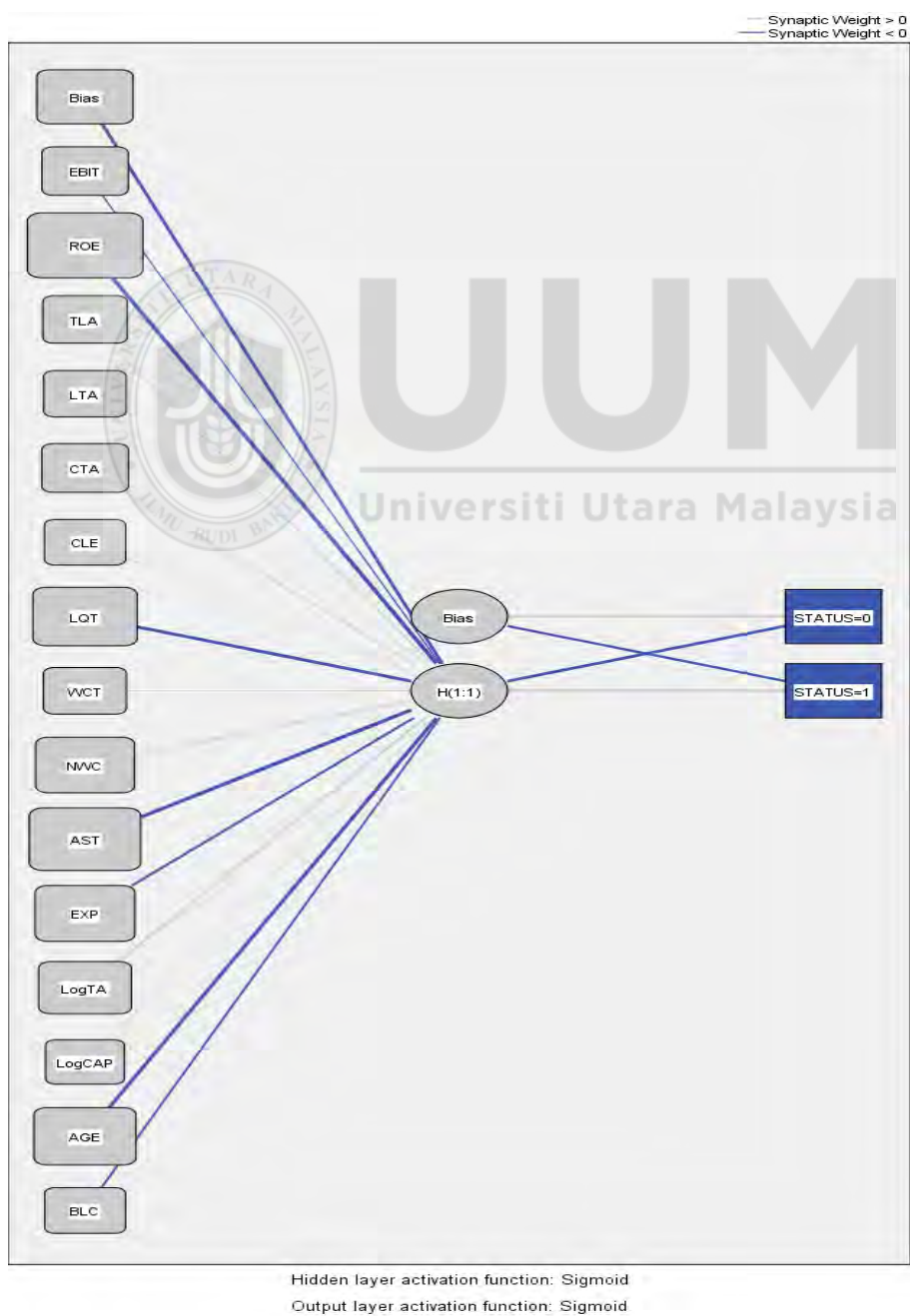
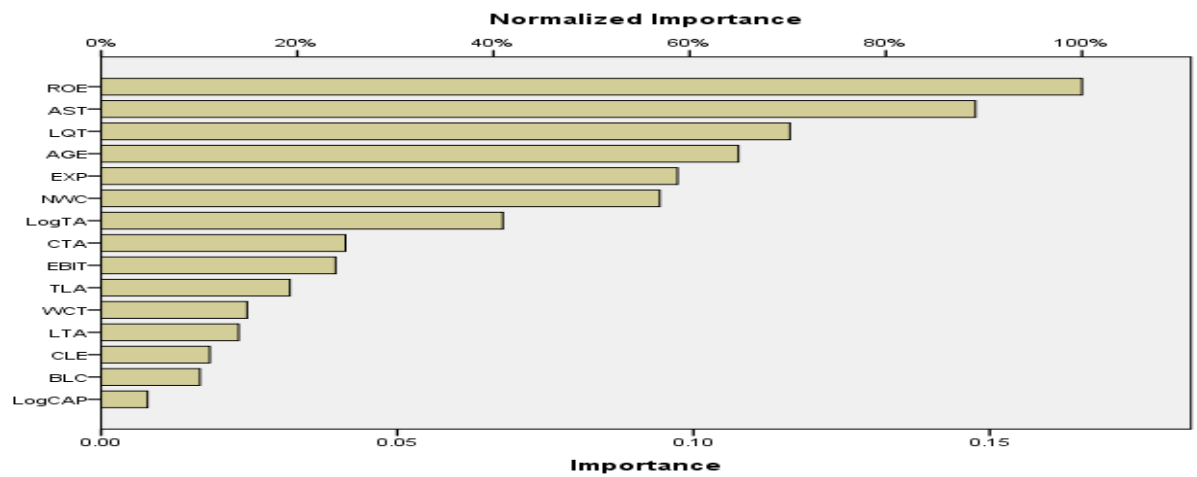
Classification

Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	157	15	91.3%
	Failed	12	151	92.6%
	Overall Percent	50.4%	49.6%	91.9%
Holdout	Non-Failed	31	7	81.6%
	Failed	3	44	93.6%
	Overall Percent	40.0%	60.0%	88.2%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
EBIT	.040	23.9%
ROE	.166	100.0%
TLA	.032	19.3%
LTA	.023	14.0%
CTA	.041	24.9%
CLE	.018	11.1%
LQT	.116	70.2%
WCT	.025	14.9%
NWC	.094	56.9%
AST	.148	89.1%
EXP	.097	58.8%
LogTA	.068	40.9%
LogCAP	.008	4.7%
AGE	.108	65.0%
BLC	.017	10.1%



APPENDIX 3h: Model 2 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	47.524
	Percent Incorrect Predictions	19.4%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.11
Holdout	Percent Incorrect Predictions	32.1%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-.799		
	GENDER	-.688		
	MDD	-1.218		
	NDIR	2.177		
	IND	-.785		
	CONT	-.843		
	CINA	-.790		
	INDIAN	-.789		
	MELAYU	-1.156		
	CPI	.035		
	GDP	-.299		
	BLR	-.473		
	EMPY	-.600		
	(Bias)		-1.796	1.798
Hidden Layer 1	H(1:1)		5.928	-5.947

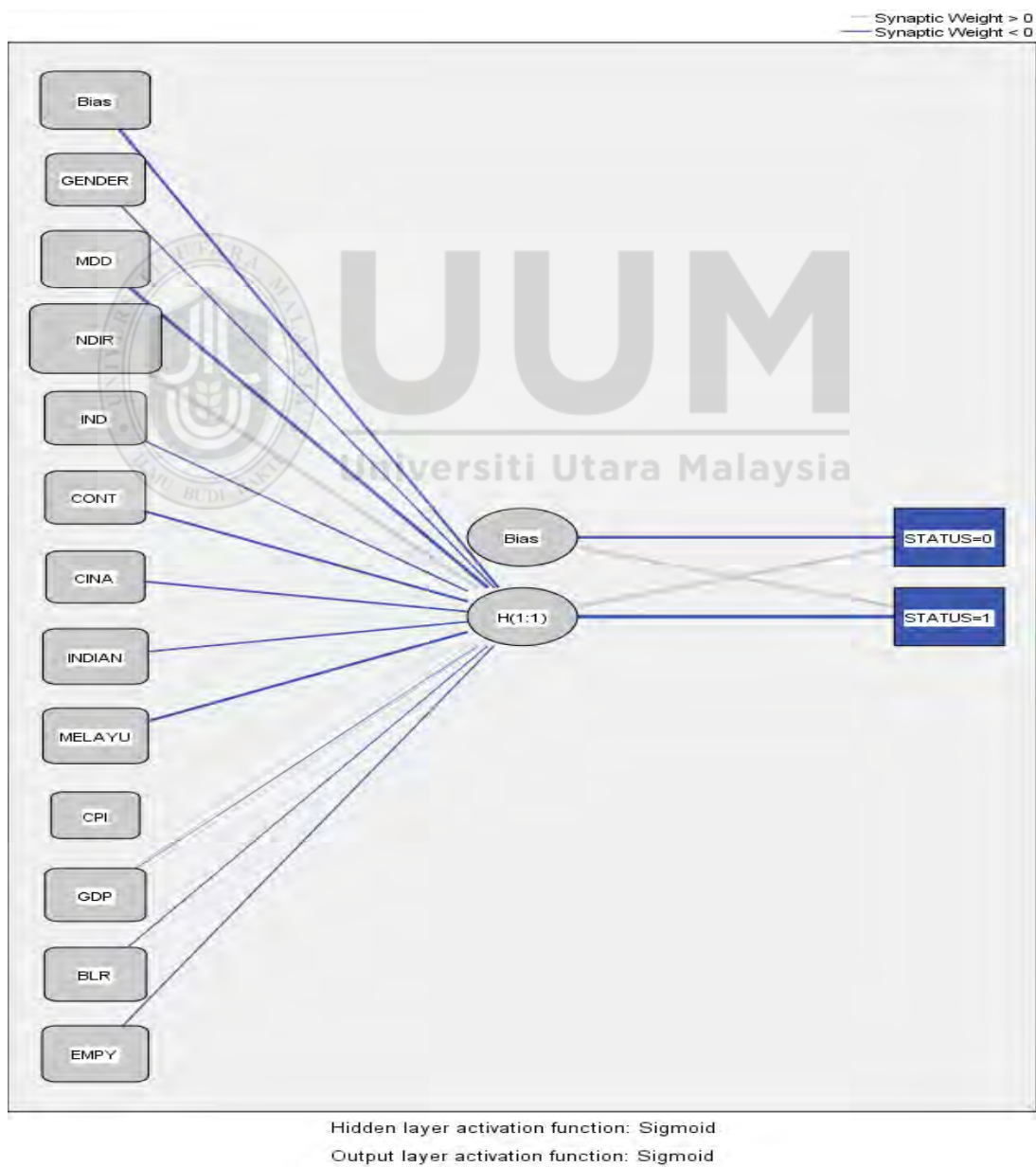
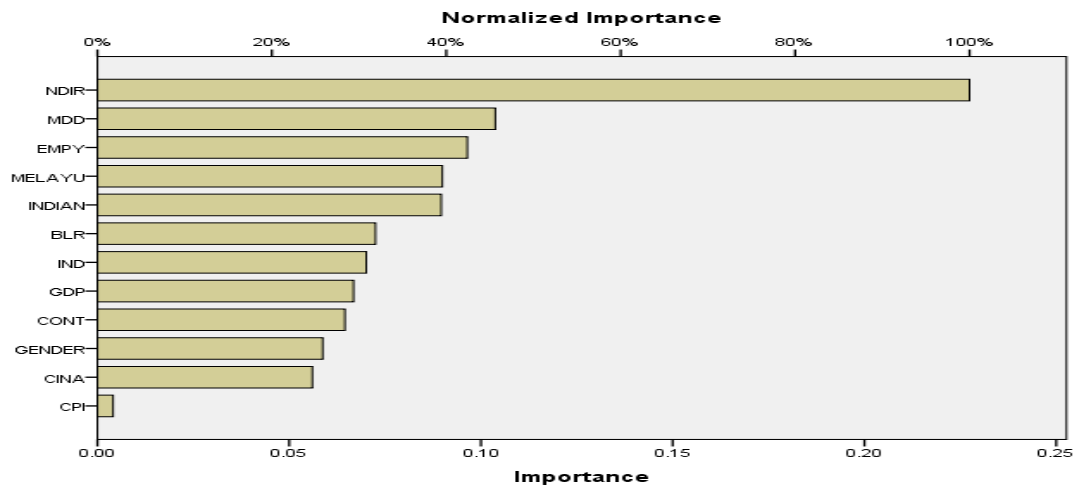
Classification

Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	138	38	78.4%
	Failed	27	132	83.0%
	Overall Percent	49.3%	50.7%	80.6%
	Non-Failed	22	12	64.7%
Holdout	Failed	15	35	70.0%
	Overall Percent	44.0%	56.0%	67.9%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.059	25.8%
MDD	.104	45.6%
NDIR	.227	100.0%
IND	.070	30.8%
CONT	.065	28.4%
CINA	.056	24.6%
INDIAN	.090	39.4%
MELAYU	.090	39.6%
CPI	.004	1.8%
GDP	.067	29.4%
BLR	.073	31.9%
EMPY	.096	42.4%



APPENDIX 3i: Model 3 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	13.084
	Percent Incorrect Predictions	4.0%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
Holdout	Training Time	0:00:00.08
	Percent Incorrect Predictions	18.3%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-2.452		
	GENDER	2.003		
	MDD	3.728		
	NDIR	-.864		
	IND	1.825		
	CONT	.183		
	CINA	1.473		
	INDIAN	2.689		
	MELAYU	2.867		
	CPI	-.228		
	GDP	1.449		
	BLR	-.006		
	EMPY	-.726		
	EBIT	-3.568		
	ROE	-7.464		
	TLA	1.697		
	LTA	.250		
	CTA	1.447		
	CLE	2.243		
	LQT	-7.673		
	WCT	-.158		
	NWC	-1.413		
	AST	-6.896		
	EXP	-3.158		
	LogTA	2.202		
	LogCAP	-.547		
	AGE	-4.346		
	BLC	.034		
Hidden Layer 1	(Bias)		4.564	-4.563
	H(1:1)		-9.493	9.493

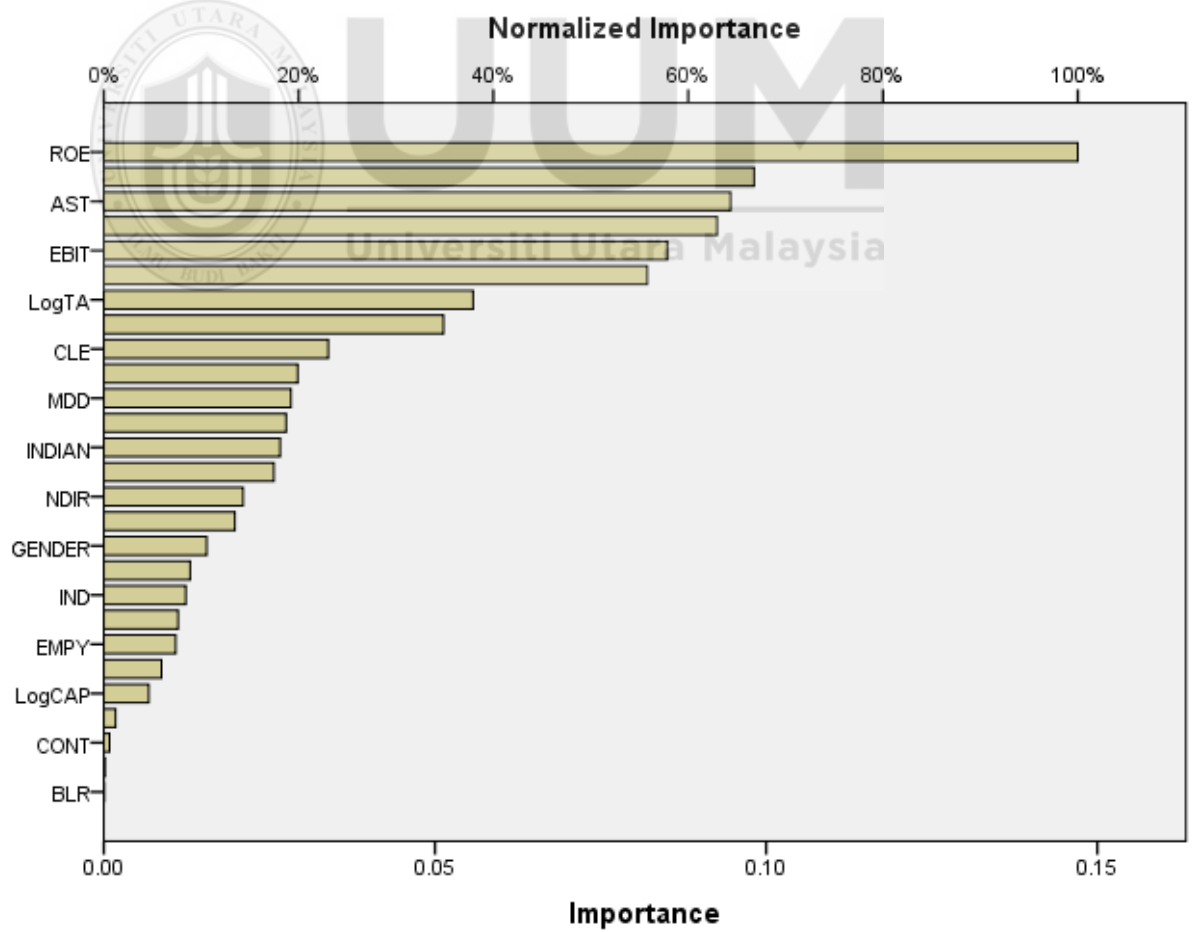
Classification

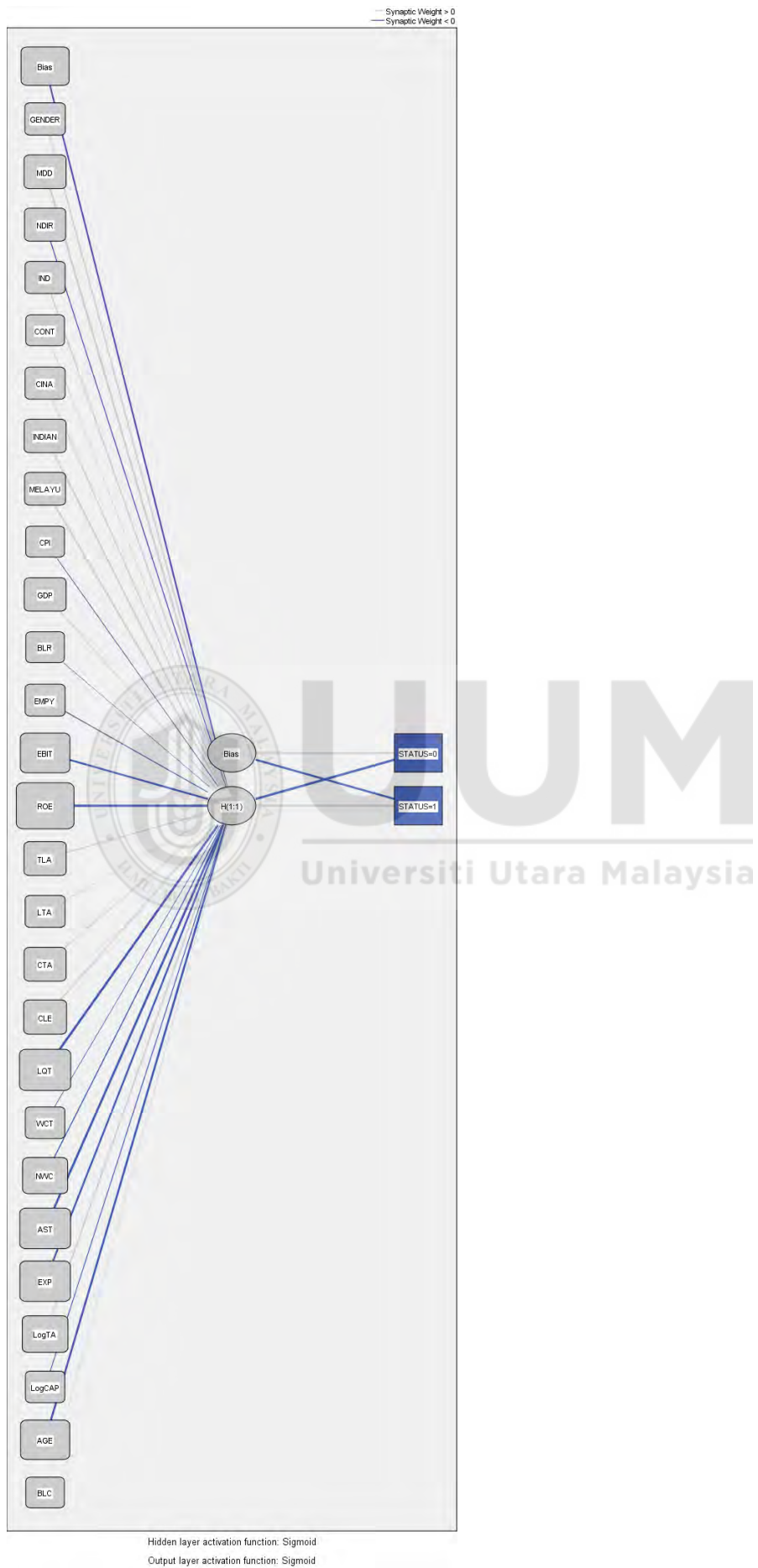
Sample	Observed	Predicted		
		Non-Failed	Failed	Percent Correct
Training	Non-Failed	153	7	95.6%
	Failed	6	160	96.4%
	Overall Percent	48.8%	51.2%	96.0%
Holdout	Non-Failed	40	10	80.0%
	Failed	7	36	83.7%
	Overall Percent	50.5%	49.5%	81.7%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GENDER	.016	10.6%
MDD	.028	19.2%
NDIR	.021	14.3%
IND	.012	8.4%
CONT	.001	0.6%
CINA	.013	8.9%
INDIAN	.027	18.1%
MELAYU	.020	13.5%
CPI	.002	1.2%
GDP	.026	17.5%
BLR	6.373E-005	0.0%
EMPY	.011	7.4%
EBIT	.085	57.8%
ROE	.147	100.0%
TLA	.029	19.9%
LTA	.011	7.6%
CTA	.028	18.7%
CLE	.034	23.0%
LQT	.098	66.8%
WCT	.009	5.9%
NWC	.051	34.9%
AST	.095	64.3%
EXP	.093	63.0%
LogTA	.056	37.9%
LogCAP	.007	4.6%
AGE	.082	55.8%
BLC	.000	0.1%





APPENDIX 4: Logistic Regression for Nigerian Sample

APPENDIX 4a: Model 1 (3-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	102.141 ^a	.663	.884

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.687	8	.989

Classification Table^a

	Observed	Predicted		
		Distress Status		Percentage Correct
		Non-Failed SME	Failed SME	
Step 1	Distress Status	159	12	93.0
	Non-Failed SME	10	162	94.2
	Overall Percentage			93.6

a. The cut value is .500

Logistic regression Number of obs = 343
 LR chi2(15) = 371.56
 Prob > chi2 = 0.0000
 Log likelihood = -51.969243 Pseudo R2 = 0.7814

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ebit	-14.81477	2.893176	-5.12	0.000	-20.4853	-9.144254
roe	-9.343665	4.957645	-1.88	0.059	-19.06047	.3731406
tla	1.986666	.5651198	3.52	0.000	.8790516	3.09428
lta	4.288052	1.152826	3.72	0.000	2.028555	6.547549
cla	-.3375677	.5911981	-0.57	0.568	-1.496295	.8211594
cle	3.076276	1.585738	1.94	0.052	-.0317136	6.184265
lqt	-.7059954	.3133853	-2.25	0.024	-1.320219	-.0917714
wct	.5740134	.841813	0.68	0.495	-1.07591	2.223937
nwc	-.0003062	.0009288	-0.33	0.742	-.0021266	.0015142
ast	.1976007	.2588676	0.76	0.445	-.3097705	.7049719
exp	2.214325	1.062919	2.08	0.037	.1310423	4.297607
logta	.1076997	.2131937	0.51	0.613	-.3101523	.5255518
logcap	-.0718521	.1945108	-0.37	0.712	-.4530861	.309382
age	-.1168695	.0321734	-3.63	0.000	-.1799281	-.0538108
blc	-1.487742	.5663296	-2.63	0.009	-2.597727	-.3777561
_cons	37.68313	13.91575	2.71	0.007	10.40877	64.95749

Note: 2 failures and 14 successes completely determined.
 linktest

Iteration 0: log likelihood = -237.74803
 Iteration 1: log likelihood = -61.352034
 Iteration 2: log likelihood = -57.509867
 Iteration 3: log likelihood = -51.916262

Logistic regression	Number of obs	=	343
	LR chi2(2)	=	371.76
	Prob > chi2	=	0.0000
Log likelihood = -51.868023	Pseudo R2	=	0.7818

Brier score	0.0467	
Spiegelhalter's z-statistic	0.3171	p = 0.3756
Sanders-modified Brier score	0.0484	
Sanders resolution	0.0479	
Outcome index variance	0.2500	
Murphy resolution	0.2021	
Reliability-in-the-small	0.0005	
Forecast variance	0.2054	
Excess forecast variance	0.0384	
Minimum forecast variance	0.1671	
Reliability-in-the-large	0.0000	
2*Forecast-Outcome-Covar	0.4087	

Classification Table^a

	Observed		Predicted		
			Distress Status		Percentage Correct
			Non-Failed SME	Failed SME	
Step 1	Distress Status	Non-Failed SME	131	41	76.2
		Failed SME	34	138	80.2
	Overall Percentage				78.2

a. The cut value is .500

Logistic regression

Number of obs = 344

LR chi2(12) = 136.16

Prob > chi2 = 0.0000

Log likelihood = -170.36381

Pseudo R2 = 0.2855

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gdp	.3000395	.3134749	0.96	0.338	-.31436	.9144391
blr	-.8913132	1.886339	-0.47	0.637	-4.588469	2.805842
cpi	.4021661	.3365866	1.19	0.232	-.2575315	1.061864
empy	44.08186	28.70929	1.54	0.125	-12.18731	100.351
gender	.6242187	.411914	1.52	0.130	-.1831178	1.431555
mdd	-.831607	.3161258	-2.63	0.009	-1.451202	-.2120119
cont	1.322251	.3486928	3.79	0.000	.638826	2.005677
ndir	-.5199817	.1040268	-5.00	0.000	-.7238705	-.3160929
ind	-2.008645	.6415269	-3.13	0.002	-3.266015	-.7512757
e1	-.2257227	.392242	-0.58	0.565	-.9945029	.5430576
e2	-.0665049	.3784845	-0.18	0.861	-.8083209	.675311
e3	-.111312	.3798789	-0.29	0.770	-.855861	.6332369
_cons	1.265376	.6315595	2.00	0.045	.0275426	2.50321

linktest

Iteration 0: log likelihood = -238.44263

Iteration 1: log likelihood = -166.40485

Iteration 2: log likelihood = -166.35454

Iteration 3: log likelihood = -166.35451

Iteration 4: log likelihood = -166.35451

Logistic regression

Number of obs = 344

LR chi2(2) = 144.18

Prob > chi2 = 0.0000

Log likelihood = -166.35451

Pseudo R2 = 0.3023

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.144705	.1277547	8.96	0.000	.8943104	1.3951
_hatsq	.1476419	.0460715	3.20	0.001	.0573434	.2379403
_cons	-.2365349	.1575777	-1.50	0.133	-.5453815	.0723116

brier status var28

Mean probability of outcome of forecast 0.5000

Correlation 0.6079

ROC area 0.8492 p = 0.0000

Brier score 0.1577

Spiegelhalter's z-statistic -0.5798 p = 0.7190

Sanders-modified Brier score 0.1584

Sanders resolution 0.1535

Outcome index variance 0.2500

Murphy resolution 0.0965

Reliability-in-the-small 0.0049

Forecast variance 0.0864

Excess forecast variance 0.0545
 Minimum forecast variance 0.0319
 Reliability-in-the-large 0.0000
 2*Forecast-Outcome-Covar 0.1787

APPENDIX 4c: Model 3 (3-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	73.339 ^a	.690	.921

a. Estimation terminated at iteration number 12 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	3.302	8	.914

Classification Table^a

	Observed	Predicted		
		Distress Status		Percentage Correct
		Non-Failed SME	Failed SME	
Step 1	Distress Status	165	6	96.5
	Non-Failed SME	9	163	94.8
	Overall Percentage			95.6

a. The cut value is .500

Logistic regression Number of obs = 343
 LR chi2 (27) = 409.04
 Prob > chi2 = 0.0000
 Log likelihood = -33.228781 Pseudo R2 = 0.8602

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gdp	.7781117	1.035236	0.75	0.452	-1.250914	2.807138
blr	-3.775473	6.597212	-0.57	0.567	-16.70577	9.154824
cpi	1.645049	1.417209	1.16	0.246	-1.13263	4.422727
empy	298.8987	115.6517	2.58	0.010	72.22542	525.5719
gender	-2.528492	1.317299	-1.92	0.055	-5.110351	.0533662
mdd	.8092365	.9169466	0.88	0.377	-.9879457	2.606419
cont	1.478152	1.0987	1.35	0.179	-.6752618	3.631565
ndir	-.6306661	.2539718	-2.48	0.013	-1.128442	-.1328906
ind	-5.518254	2.443208	-2.26	0.024	-10.30685	-.7296537
e1	3.943827	1.759436	2.24	0.025	.4953953	7.392258
e2	3.371608	1.555307	2.17	0.030	.3232629	6.419953
e3	.7737331	1.144702	0.68	0.499	-1.469841	3.017307
cla	-1.454535	.9595861	-1.52	0.130	-3.335289	.4262192
ebit	-28.48281	7.02667	-4.05	0.000	-42.25483	-14.71079
roe	-22.07524	8.799247	-2.51	0.012	-39.32144	-4.829028
tla	3.845466	1.143543	3.36	0.001	1.604163	6.08677
lta	7.567882	2.243217	3.37	0.001	3.171258	11.96451
cle	8.16124	3.291742	2.48	0.013	1.709544	14.61294
lqt	-1.267447	.4777916	-2.65	0.008	-2.203902	-.3309929
wct	1.055695	1.66393	0.63	0.526	-2.205549	4.316939
nwc	-.0007598	.0010365	-0.73	0.464	-.0027913	.0012716
ast	.11924	.4428877	0.27	0.788	-.748804	.987284
exp	3.094696	1.76528	1.75	0.080	-.3651889	6.554581
logta	-.3953828	.3553073	-1.11	0.266	-1.091772	.3010067
logcap	.6995847	.3750572	1.87	0.062	-.035514	1.434683
age	-.1394117	.0488611	-2.85	0.004	-.2351778	-.0436457
blc	-3.50795	1.196626	-2.93	0.003	-5.853294	-1.162606

```

      _cons |   80.64021   26.99968    2.99   0.003   27.72182   133.5586
-----+-----
Note: 15 failures and 48 successes completely determined.

```

linktest

```

Iteration 0:  log likelihood = -237.74803
Iteration 1:  log likelihood = -48.660965
Iteration 2:  log likelihood = -36.128191
Iteration 3:  log likelihood = -33.46796
Iteration 4:  log likelihood = -33.053255
Iteration 5:  log likelihood = -33.046501
Iteration 6:  log likelihood = -33.045804
Iteration 7:  log likelihood = -33.045792
Iteration 8:  log likelihood = -33.045792

```

```

Logistic regression                                Number of obs   =       343
                                                    LR chi2(2)      =      409.40
                                                    Prob > chi2     =      0.0000
Log likelihood = -33.045792                      Pseudo R2      =      0.8610

```

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	1.013617	.188226	5.39	0.000	.6447004 1.382533
_hatsq	.0100832	.0032866	3.07	0.249	.0036416 .0165247
_cons	-.0269479	.313085	-0.09	0.931	-.6405831 .5866873

brier status var29

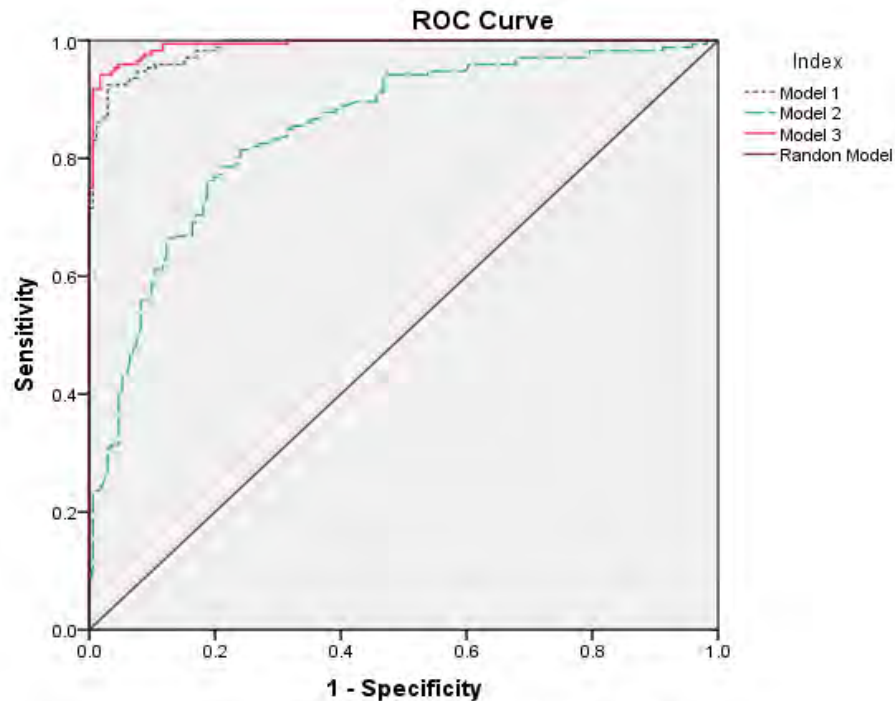
```

Mean probability of outcome 0.5015
of forecast 0.5015

Correlation 0.9355
ROC area 0.9927 p = 0.0000

Brier score 0.0312
Spiegelhalter's z-statistic -0.3218 p = 0.6262
Sanders-modified Brier score 0.0366
Sanders resolution 0.0363
Outcome index variance 0.2500
Murphy resolution 0.2137
Reliability-in-the-small 0.0003
Forecast variance 0.2170
Excess forecast variance 0.0271
Minimum forecast variance 0.1899
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.4358

```



Diagonal segments are produced by ties.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Model 1	.987	.004	.000	.979	.995
Model 2	.848	.021	.000	.808	.889
Model 3	.993	.003	.000	.987	.998

The test result variable(s): Model 2 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

APPENDIX 4d: Model 1 (2-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	111.384 ^a	.522	.696

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	9.919	8	.271

Classification Table^a

	Observed		Predicted		
			Distress status		Percentage Correct
			Non-failed SME	Failed SME	
Step 1	Distress status	Non-failed SME	74	12	86.0
		Failed SME	13	73	84.9
	Overall Percentage				85.5

a. The cut value is .500

Logistic regression

Number of obs = 172
 LR chi2(15) = 127.13
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.5332

Log likelihood = -55.654473

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	-.2180605	.0469631	-4.64	0.000	-.3101065	-.1260144
b1c	-1.227612	.5258931	-2.33	0.020	-2.258343	-.1968803
lgta	.3831998	.2457099	1.56	0.119	-.0983827	.8647823
lgcap	.4136951	.2182157	1.90	0.058	-.0139999	.84139
t1a	.3580774	.1894363	1.89	0.059	-.013211	.7293658
lta	-1.236607	1.379089	-0.90	0.370	-3.939573	1.466358
cla	2.16186	1.655647	1.31	0.192	-1.083149	5.40687
cle	.4030159	.2791147	1.44	0.149	-.1440388	.9500707
lqt	-.0654955	.0737803	-0.89	0.375	-.2101023	.0791113
exp	.2913615	.2686249	1.08	0.278	-.2351335	.8178565
ebit	-10.04817	2.698211	-3.72	0.000	-15.33657	-4.759778
roe	.2336491	.2096197	1.11	0.265	-.177198	.6444963
wct	-1.431815	.6675135	-2.14	0.032	-2.740118	-.1235129
nwc	-.0007595	.0017066	-0.45	0.656	-.0041043	.0025853
ast	-.3127946	.2306252	-1.36	0.175	-.7648117	.1392225
_cons	-7.540194	5.671835	-1.33	0.184	-18.65679	3.576398

Note: 0 failures and 3 successes completely determined.

linktest

Iteration 0: log likelihood = -119.22132
 Iteration 1: log likelihood = -57.016168
 Iteration 2: log likelihood = -56.328997
 Iteration 3: log likelihood = -55.352828
 Iteration 4: log likelihood = -54.417811
 Iteration 5: log likelihood = -54.403157
 Iteration 6: log likelihood = -54.403141
 Iteration 7: log likelihood = -54.403141

Logistic regression

Number of obs = 172
 LR chi2(2) = 129.64
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.5437

Log likelihood = -54.403141

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.082075	.1777958	6.09	0.000	.7336018	1.430548
_hatsq	.0851371	.0478801	1.78	0.075	-.0087062	.1789803
_cons	-.1985104	.2701223	-0.73	0.462	-.7279403	.3309196

brier status var31

Mean probability of outcome 0.5000
 of forecast 0.5000

Correlation 0.7759
 ROC area 0.9336 p = 0.0000

Brier score 0.0995

Spiegelhalter's z-statistic -0.1989 p = 0.5788
 Sanders-modified Brier score 0.1045
 Sanders resolution 0.1004
 Outcome index variance 0.2500
 Murphy resolution 0.1496
 Reliability-in-the-small 0.0041
 Forecast variance 0.1479
 Excess forecast variance 0.0589
 Minimum forecast variance 0.0890
 Reliability-in-the-large 0.0000
 2*Forecast-Outcome-Covar 0.2983

APPENDIX 4e: Model 2 (2-year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	91.068 ^a	.575	.767

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	3.032	8	.932

Classification Table^a

	Observed	Predicted			
		Distress status		Percentage Correct	
		Non-failed SME	Failed SME		
Step 1	Distress status	Non-failed SME	74	12	86.0
		Failed SME	8	78	90.7
	Overall Percentage				88.4

a. The cut value is .500

Logistic regression

Number of obs = 172
 LR chi2(12) = 147.38
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.6181

Log likelihood = -45.533751

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ind	-1.546551	1.174787	-1.32	0.188	-3.84909	.7559884
gender	2.716002	.8000033	3.39	0.001	1.148024	4.283979
cont	3.985585	.720986	5.53	0.000	2.572478	5.398691
ndir	-1.747891	.4231401	-4.13	0.000	-2.57723	-.9185511
mdd	-.8365568	.7251241	-1.15	0.249	-2.257774	.5846604
e1	.8623743	.8555602	1.01	0.313	-.8144929	2.539242
e2	.6941031	.7742187	0.90	0.370	-.8233377	2.211544
e3	-.2987867	.8202987	-0.36	0.716	-1.906543	1.308969
gdp	.0181561	.6312158	0.03	0.977	-1.219004	1.255316
blr	5.879454	3.911953	1.50	0.133	-1.787834	13.54674
cpi	1.032575	.852981	1.21	0.226	-.6392368	2.704387
empy	153.7456	68.88561	2.23	0.026	18.7323	288.7589
_cons	.5637957	1.419655	0.40	0.691	-2.218676	3.346268

linktest

Iteration 0: log likelihood = -119.22132

Logistic regression	Number of obs	=	172
	LR chi2(2)	=	147.38
	Prob > chi2	=	0.0000
Log likelihood = -45.53278	Pseudo R2	=	0.6181

```
brier status var32
```

Correlation	0.8125	
ROC area	0.9562	p = 0.0000

Brier score	0.0850	
Spiegelhalter's z-statistic	0.3307	p = 0.3704
Sanders-modified Brier score	0.0837	
Sanders resolution	0.0826	
Outcome index variance	0.2500	
Murphy resolution	0.1674	
Reliability-in-the-small	0.0011	
Forecast variance	0.1693	
Excess forecast variance	0.0575	
Minimum forecast variance	0.1118	
Reliability-in-the-large	0.0000	
2*Forecast-Outcome-Covar	0.3343	

APPENDIX 4f: Model 3 (2-year Prior Sub-sample)

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	35.958 ^a	.692	.922

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.271	8	.996

Classification Table					
		Observed	Predicted		
			Distress status		Percentage Correct
			Non-failed SME	Failed SME	
Step 1	Distress status	Non-failed SME	81	5	94.2
		Failed SME	4	82	95.3

Overall Percentage			94.8
--------------------	--	--	------

Logistic regression

Log likelihood = -18.574994

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gender	3.430917	1.576678	2.18	0.030	.3406851	6.52115
cont	6.193857	2.009947	3.08	0.002	2.254433	10.13328
ndir	-1.212266	.5705787	-2.12	0.034	-2.33058	-.0939522
cpi	4.531204	2.368695	1.91	0.056	-.1113536	9.173761
empy	81.41484	199.9869	0.41	0.684	-310.5523	473.3819
age	-.3146806	.1222658	-2.57	0.010	-.5543172	-.0750441
blc	-4.332444	2.151373	-2.01	0.044	-8.549057	-.1158306
lgta	.6029914	.6350999	0.95	0.342	-.6417814	1.847764
lgcap	.9968369	.5051603	1.97	0.048	.006741	1.986933
tla	1.015187	.5443217	1.87	0.062	-.0516642	2.082038
lta	-2.709361	3.816789	-0.71	0.478	-10.19013	4.771408
cla	4.451715	5.872275	0.76	0.448	-7.057732	15.96116
cle	1.116134	.6379086	1.75	0.080	-.1341443	2.366411
lqt	-.1710179	.2182284	-0.78	0.433	-.5987376	.2567019
exp	-.3468902	.6013186	-0.58	0.564	-1.525453	.8316726
ebit	-17.79112	8.03998	-2.21	0.027	-33.54919	-2.033049
roe	.4927496	.483602	1.02	0.308	-.4550929	1.440592
wct	-3.311312	2.01632	-1.64	0.101	-7.263225	.6406021
nwc	.0001758	.003053	0.06	0.954	-.0058078	.0061595
ast	.1680873	.6261737	0.27	0.788	-1.059191	1.395365
_cons	-22.05732	15.86291	-1.39	0.164	-53.14804	9.033404

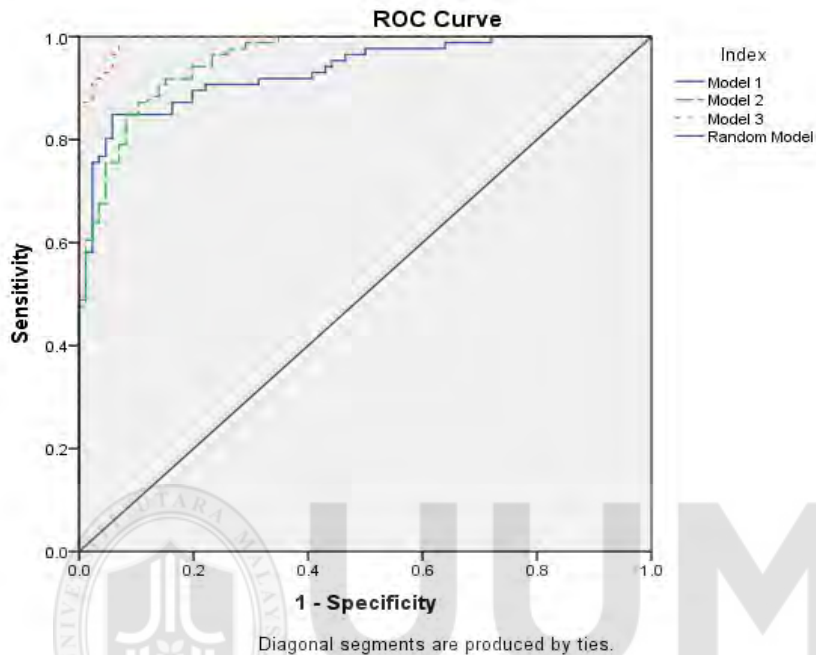
linktest

Logistic regression

	status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
	_hat	1.000229	.4415247	2.27	0.023	.1348568 1.865602
	_hatsq	.0048077	.137785	0.03	0.972	-.2652459 .2748614
	_cons	-.0068958	.5651181	-0.01	0.990	-1.114507 1.100715

Mean probability of outcome	0.5000
of forecast	0.5000

Spiegelhalter's z-statistic 0.3950 p = 0.3464
 Sanders-modified Brier score 0.0438
 Sanders resolution 0.0415
 Outcome index variance 0.2500
 Murphy resolution 0.2085
 Reliability-in-the-small 0.0023
 Forecast variance 0.2226
 Excess forecast variance 0.0270
 Minimum forecast variance 0.1955
 Reliability-in-the-large 0.0000
 2*Forecast-Outcome-Covar 0.4422



Area Under the Curve

Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Model 1	.934	.019	.000	.897	.970
Model 2	.956	.013	.000	.930	.982
Model 3	.994	.003	.000	.987	1.000

The test result variable(s): Model 2 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

APPENDIX 4g: Model 1 (1-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	72.141 ^a	.534	.713

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	3.932	8	.863

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed SME	
Step 1	STATUS Non-Failed	51	7	87.9
	Failed SME	10	48	82.8
	Overall Percentage			85.3

a. The cut value is .500

Logistic regression

Number of obs = 116
 LR chi2(15) = 88.57
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.5508

Log likelihood = -36.119583

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
age	-.2942693	.0725098	-4.06	0.000	-.436386	-.1521527
blc	-1.650828	.6699368	-2.46	0.014	-2.96388	-.3377755
lgta	.6612721	.3441357	1.92	0.055	-.0132216	1.335766
lgcapital	-.2558692	.2878073	-0.89	0.374	-.8199612	.3082227
tla	.4237849	.2314139	1.83	0.067	-.029778	.8773478
lta	-.0772941	1.038988	-0.07	0.941	-2.113673	1.959085
cle	2.323212	2.44723	0.95	0.342	-2.473271	7.119695
lqt	-.1729614	.0840469	-2.06	0.040	-.3376902	-.0082326
cla	-.4844375	.593958	-0.82	0.415	-1.648574	.6796988
ebit	-8.967879	3.224262	-2.78	0.005	-15.28732	-2.648442
roe	-.0724758	.208796	-0.35	0.729	-.4817085	.3367569
wct	-.3960157	.7083895	-0.56	0.576	-1.784434	.9924021
nwc	-.0022089	.0020675	-1.07	0.285	-.0062611	.0018432
ast	-1.093875	.4158403	-2.63	0.009	-1.908907	-.2788429
exp	5.016023	2.376801	2.11	0.035	.357579	9.674467
_cons	-2.417662	6.436262	-0.38	0.707	-15.0325	10.19718

Note: 0 failures and 1 success completely determined.

linktest

Iteration 0: log likelihood = -80.405073
 Iteration 1: log likelihood = -36.801705
 Iteration 2: log likelihood = -36.147099
 Iteration 3: log likelihood = -35.540111
 Iteration 4: log likelihood = -35.367351
 Iteration 5: log likelihood = -35.361971
 Iteration 6: log likelihood = -35.361964
 Iteration 7: log likelihood = -35.361964

Logistic regression

Number of obs = 116
 LR chi2(2) = 90.09
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.5602

Log likelihood = -35.361964

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.081144	.2299742	4.70	0.000	.6304032	1.531885
_hatsq	.0710064	.0452277	1.57	0.116	-.0176381	.159651

```

      _cons |  -0.1416514   .3170945   -0.45   0.655   -0.7631453   .4798424
-----+-----
brier status var27

Mean probability of outcome    0.5000
      of forecast              0.5000

Correlation                    0.7745
ROC area                      0.9364   p = 0.0000

Brier score                    0.1000
Spiegelhalter's z-statistic   0.0440   p = 0.4824
Sanders-modified Brier score  0.1010
Sanders resolution            0.0964
Outcome index variance        0.2500
Murphy resolution             0.1536
Reliability-in-the-small      0.0046
Forecast variance             0.1506
Excess forecast variance      0.0603
Minimum forecast variance     0.0904
Reliability-in-the-large      0.0000
2*Forecast-Outcome-Covar     0.3006

```

APPENDIX 4h: Model 2 (1-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	98.003 ^a	.418	.557

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	5.650	8	.686

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed SME	
Step 1	STATUS Non-Failed	42	16	72.4
	Failed SME	4	54	93.1
	Overall Percentage			82.8

a. The cut value is .500

Variables in the Equation

		Variables in the Equation					
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a	GENDER	-.968	.597	2.628	1	.105	.380
	IND	1.272	1.990	.408	1	.523	3.567
	CONT	3.918	.692	32.026	1	.000	50.283
	NDIR	-.075	.167	.203	1	.652	.927
	MDD	-.375	.641	.342	1	.559	.687
	Hausa	-1.413	.943	2.247	1	.134	.243
	Yaroba	-.667	.879	.576	1	.448	.513
	Igbo	-1.046	.916	1.303	1	.254	.352

GDP	.253	.644	.155	1	.694	1.288
BLR	-4.489	3.606	1.550	1	.213	.011
CPI	-.323	.706	.210	1	.647	.724
EMPY	13.731	60.937	.051	1	.822	918954.646
Constant	-.914	1.025	.795	1	.373	.401

a. Variable(s) entered on step 1: SEX, IND, CONT, NDIR, DLTY, Hausa, Yaroba, Igbo, GDP, BLR, CPI, EMPY.

Log likelihood = -49.1247

Pseudo R2 = 0.3890

linktest

Iteration 0: log likelihood = -80.405073
Iteration 1: log likelihood = -49.362093
Iteration 2: log likelihood = -49.112689
Iteration 3: log likelihood = -49.110937
Iteration 4: log likelihood = -49.110937

Logistic regression

Number of obs = 116
LR chi2(2) = 62.59
Prob > chi2 = 0.0000
Pseudo R2 = 0.3892

Log likelihood = -49.110937

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_hat	.9859619	.1906251	5.17	0.000	.6123436 1.35958
_hatsq	-.0190123	.1142883	-0.17	0.868	-.2430132 .2049886
_cons	.0477352	.3873136	0.12	0.902	-.7113855 .8068558

brier status var28

Mean probability of outcome 0.5000
of forecast 0.5000

Correlation 0.6835
ROC area 0.8795 p = 0.0000

Brier score 0.1332
Spiegelhalter's z-statistic -0.0009 p = 0.5004
Sanders-modified Brier score 0.1345
Sanders resolution 0.1306
Outcome index variance 0.2500
Murphy resolution 0.1194
Reliability-in-the-small 0.0039
Forecast variance 0.1168
Excess forecast variance 0.0622
Minimum forecast variance 0.0546
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.2336

APPENDIX 4i: Model 3 (1-Year Prior Sub-sample)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	29.115 ^a	.679	.905

a. Estimation terminated at iteration number 12 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	1.273	8	.996

Classification Table^a

	Observed	Predicted		
		STATUS		Percentage Correct
		Non-Failed	Failed SME	
Step 1	STATUS Non-Failed	54	4	93.1
	Failed SME	4	54	93.1
	Overall Percentage			93.1

a. The cut value is .500

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)	
Step 1 ^a	GENDER	.039	1.413	.001	1	.978	1.039
	CONT	15.630	7.647	4.178	1	.041	6137785.824
	NDIR	-.146	.466	.098	1	.754	.864
	MDD	.147	2.167	.005	1	.946	1.158
	BLR	-33.546	14.512	5.344	1	.021	.000
	CPI	-4.527	2.964	2.332	1	.127	.011
	EMPY	514.671	287.857	3.197	1	.074	.000
	Age	-.950	.412	5.328	1	.021	.387
	BLC	-8.567	4.067	4.438	1	.035	.000
	LogTA	-2.060	1.098	3.516	1	.061	7.845
	LogCAP	-1.273	.879	2.096	1	.148	.280
	TLA	2.581	1.401	3.391	1	.066	13.208
	LTA	.479	1.632	.086	1	.769	1.615
	CLE	5.377	5.667	.900	1	.343	216.398
	LQT	-.790	.389	4.120	1	.042	.454
	CLA	-.159	1.207	.017	1	.895	.853
	EBIT	-18.996	9.416	4.070	1	.044	.000
	ROE	-1.901	.969	3.850	1	.050	.149
	WCT	-3.418	2.686	1.619	1	.203	.033
	NWC	-.030	.016	3.382	1	.066	.971
	AST	-2.481	1.122	4.890	1	.027	.084
	EXP	15.011	9.968	2.268	1	.132	3304259.539
	Constant	44.586	31.467	2.008	1	.157	2308389475201 8070000.000

a. Variable(s) entered on step 1: SEX, CONT, NDIR, DLT, BLR, CPI, EMPY, Age, BLC, lgTA, lgcapital, TLA, LTA, CLE, LQT, CLA, EBIT, ROE, WCT, NWC, AST, EXP.

Log likelihood = -13.93074

Pseudo R2 = 0.8267

linktest

Iteration 0: log likelihood = -80.405073
Iteration 1: log likelihood = -22.342667
Iteration 2: log likelihood = -15.992228
Iteration 3: log likelihood = -14.047035
Iteration 4: log likelihood = -13.943579
Iteration 5: log likelihood = -13.935092
Iteration 6: log likelihood = -13.931661
Iteration 7: log likelihood = -13.905427
Iteration 8: log likelihood = -13.905339
Iteration 9: log likelihood = -13.905339

Logistic regression

Number of obs = 116

Log likelihood = -13.905339

LR chi2(2)	=	133.00
Prob > chi2	=	0.0000
Pseudo R2	=	0.8271

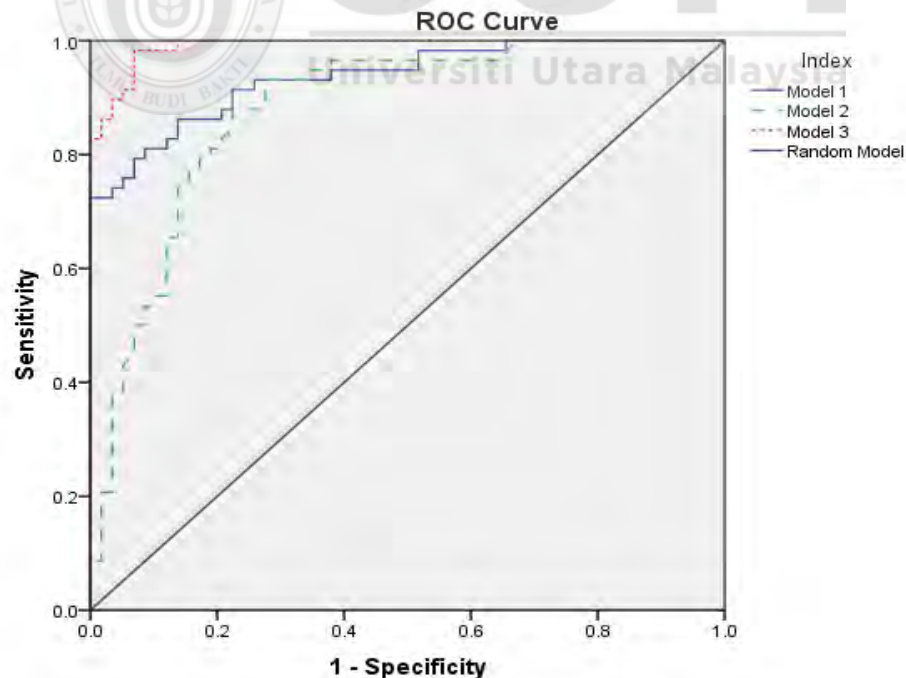
status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_hat	1.003761	.3335444	3.01	0.003	.3500263	1.657496
_hatsq	-.0097927	.0079039	-1.24	0.215	-.0252841	.0056986
_cons	.0202594	.4748968	0.04	0.966	-.9105211	.95104

brier status var29

Mean probability of outcome 0.5000
of forecast 0.5000

Correlation 0.9140
ROC area 0.9902 p = 0.0000

Brier score 0.0411
Spiegelhalter's z-statistic 0.0870 p = 0.4653
Sanders-modified Brier score 0.0464
Sanders resolution 0.0449
Outcome index variance 0.2500
Murphy resolution 0.2051
Reliability-in-the-small 0.0015
Forecast variance 0.2097
Excess forecast variance 0.0345
Minimum forecast variance 0.1752
Reliability-in-the-large 0.0000
2*Forecast-Outcome-Covar 0.4186



Diagonal segments are produced by ties.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Model 1	.936	.021	.000	.894	.978
Model 2	.879	.032	.000	.816	.943
Model 3	.990	.006	.000	.979	1.000

The test result variable(s): Model 2 has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

APPENDIX 5a: 3-year Prior To bankruptcy sample endogeneity test

Model 2

NDIR

First-stage regressions

```
reg ndir gender mdd cont ind e2 e3 e4 gdp blr cpi empy l_ind_ndir
```

Source	SS	df	MS	Number of obs =	344
Model	554.753857	12	46.2294881	F(12, 331) =	14.85
Residual	1030.40603	331	3.11300914	Prob > F =	0.0000
Total	1585.15988	343	4.62145739	R-squared =	0.3500
				Adj R-squared =	0.3264
				Root MSE =	1.7644

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	-.2273915	.2928659	-0.78	0.438	-.8035046 .3487216
mdd	-.0950929	.2186479	-0.43	0.664	-.5252076 .3350217
cont	-1.194331	.2289077	-5.22	0.000	-1.644628 -.7440335
ind	4.019464	.3940009	10.20	0.000	3.244403 4.794526
e2	.2276301	.280728	0.81	0.418	-.3246059 .7798661
e3	-.1816774	.2916496	-0.62	0.534	-.7553979 .3920432
e4	-.2119507	.2829846	-0.75	0.454	-.7686258 .3447244
gdp	-.0662231	.2063464	-0.32	0.748	-.4721388 .3396925
blr	.3867293	1.364292	0.28	0.777	-2.297047 3.070506
cpi	-.1756235	.2434041	-0.72	0.471	-.6544376 .3031906
empy	4.682483	19.64086	0.24	0.812	-33.95417 43.31913
l_ind_ndir	.5910019	.4650522	1.27	0.005	-.3238287 1.505833
_cons	3.205699	.80841	3.97	0.000	1.61543 4.795968

```
. predict ndirH
(option xb assumed; fitted values)
```

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 21.5668 (p = 0.0000)
Wu-Hausman F(1,330) = 22.0729 (p = 0.0000)

```
. estat firststage, all
```

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .170784 (p = 0.6794)
Basman chi2(1) = .163915 (p = 0.6856)

IND

First-stage regressions

```
. reg ind gender mdd cont ndir e2 e3 e4 gdp blr cpi empy l_ind_ind
```

Source	SS	df	MS	Number of obs	=	344
Model	6.2360164	12	.519668034	F(12, 331)	=	11.26
Residual	15.2822126	331	.046169827	Prob > F	=	0.0000
				R-squared	=	0.2898
				Adj R-squared	=	0.2641
Total	21.518229	343	.062735362	Root MSE	=	.21487

ind	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	-.00271	.0351588	-0.08	0.939	-.0718729 .0664528
mdd	-.0044709	.0266245	-0.17	0.867	-.0568455 .0479038
cont	.0537389	.0286982	1.87	0.062	-.0027148 .1101927
ndir	.0598791	.0058255	10.28	0.000	.0484194 .0713388
e2	-.0510017	.0340945	-1.50	0.136	-.118071 .0160675
e3	-.0613808	.0354169	-1.73	0.084	-.1310514 .0082898
e4	-.0484246	.0343739	-1.41	0.160	-.1160435 .0191943
gdp	-.0434368	.0249726	-1.74	0.083	-.0925619 .0056883
blr	.2246308	.1655838	1.36	0.176	-.1010986 .5503602
cpi	-.0224238	.0296366	-0.76	0.450	-.0807236 .0358761
empy	-2.161719	2.379299	-0.91	0.364	-6.842174 2.518736
l_ind_ind	.561148	.025504	0.24	0.015	-.0440556 .0562852
_cons	.0184235	.064514	0.29	0.775	-.1084857 .1453328

```
. predict indH
(option xb assumed; fitted values)
```

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 6.46892 (p = 0.0110)

Wu-Hausman F(1,330) = 6.32459 (p = 0.0124)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .052595 (p = 0.8186)

Basman chi2(1) = .050462 (p = 0.8223)

SECOND STAGE

```
. logit status gender mdd cont ndirH indH e2 e3 e4 gdp blr cpi empy
```

```
Iteration 0: log likelihood = -238.44263
Iteration 1: log likelihood = -168.95598
Iteration 2: log likelihood = -167.79848
Iteration 3: log likelihood = -167.79461
Iteration 4: log likelihood = -167.79461
```

Logistic regression	Number of obs	=	344
	LR chi2(12)	=	141.30
	Prob > chi2	=	0.0000
Log likelihood = -167.79461	Pseudo R2	=	0.2963

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender	.4448144	.4181924	1.06	0.287	-.3748277 1.264457
mdd	-.9449865	.322773	-2.93	0.003	-1.57761 -.3123631
cont	1.097115	.3754541	2.92	0.003	.3612382 1.832991
ndirH	-.5841712	.1611154	-3.63	0.000	-.8999516 -.2683908
indH	-8.333817	1.747108	-4.77	0.000	-11.75809 -4.909549
e2	-.1518455	.4100129	-0.37	0.011	-.9554559 .651765

e3		-.5238061	.4406227	-1.19	0.035	-1.387411	.3397986
e4		-.322022	.4076041	-0.79	0.430	-1.120911	.4768673
gdp		-.0948991	.330121	-0.29	0.774	-.7419244	.5521262
blr		1.334583	1.961944	0.68	0.496	-2.510756	5.179922
cpi		.1113812	.3416359	0.33	0.744	-.5582129	.7809752
empy		30.29977	29.23856	1.04	0.030	-27.00676	87.6063
_cons		3.50945	.9255976	3.79	0.000	1.695313	5.323588

MDD

First-stage regressions

							Number of obs	=	344
							F(13, 330)	=	6.37
							Prob > F	=	0.0000
							R-squared	=	0.2006
							Adj R-squared	=	0.1691
							Root MSE	=	0.4439
mdd		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]			
gdp		-.0192885	.0518449	-0.37	0.710	-.1212767	.0826997		
blr		.3882816	.3420974	1.14	0.257	-.284685	1.061248		
cpi		.0307711	.0614534	0.50	0.617	-.0901187	.151661		
empy		2.524137	4.931704	0.51	0.609	-7.177405	12.22568		
gender		.0149425	.0723754	0.21	0.837	-.1274329	.1573178		
ndir		-.0056834	.0138638	-0.41	0.682	-.0329559	.0215892		
cont		.3895723	.0558588	6.97	0.000	.2796881	.4994565		
ind		-.0214638	.113737	-0.19	0.850	-.2452047	.2022771		
e2		.0909489	.0705026	1.29	0.198	-.0477424	.2296401		
e3		.1488045	.0729722	2.04	0.042	.0052551	.2923539		
e4		.2291819	.0701024	3.27	0.001	.091278	.3670858		
l_dirown		.0108643	.0410176	0.26	0.791	-.0698247	.0915533		
l_tngasset		-.0209786	.0328485	-0.64	0.523	-.0855976	.0436403		
_cons		.0036528	.124719	0.03	0.977	-.2416917	.2489974		

Instrumental variables (2SLS) regression

		Number of obs	=	344
		Wald chi2(12)	=	141.45
		Prob > chi2	=	0.0000
		R-squared	=	0.2423
		Root MSE	=	.43522

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]		
mdd		-.4717455	1.418465	-0.33	0.739	-3.251886	2.308395	
gdp		.0452101	.056963	0.79	0.427	-.0664354	.1568557	
blr		-.026021	.6390218	-0.04	0.968	-1.278481	1.226439	
cpi		.0819587	.0766677	1.07	0.285	-.0683072	.2322246	
empy		8.022226	6.207113	1.29	0.196	-4.143492	20.18794	
gender		.1366262	.0737174	1.85	0.064	-.0078573	.2811096	
ndir		-.0750445	.0156381	-4.80	0.000	-.1056945	-.0443945	
cont		.3724887	.5510883	0.68	0.499	-.7076244	1.452602	
ind		-.4006331	.1145586	-3.50	0.000	-.6251638	-.1761024	
e2		.0531664	.1442959	0.37	0.713	-.2296483	.3359812	
e3		.0564716	.2203309	0.26	0.798	-.3753692	.4883123	
e4		.1204651	.3298481	0.37	0.715	-.5260253	.7669554	
_cons		.630394	.1144642	5.51	0.000	.4060483	.8547396	

Instrumented: mdd

Instruments: gdp blr cpi empy gender ndir cont ind e2 e3 e4 l_dirown
l_tngasset

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .061822 (p = 0.8036)

Wu-Hausman F(1,330) = .059317 (p = 0.8077)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .719866 (p = 0.3962)

Basman chi2(1) = .692017 (p = 0.4055)


```

      ind | -.2243005   .0965031   -2.32   0.020   -.4134431   -.0351578
      e1 | -.0910449   .4373304   -0.21   0.835   -.9481966   .7661069
      e2 | -.0479915   .2967578   -0.16   0.872   -.6296261   .533643
      e3 | -.0707659   .1752634   -0.40   0.686   -.4142758   .272744
      _cons | 1.071437   .7448493   1.44   0.150   -.3884407   2.531315
-----+-----
Instrumented: mdd
Instruments:  cla ebit roe tla lta cle lqt wct nwc ast exp logta logcap gdp
              blr cpi empy age blc gender cont ndir ind e1 e2 e3 l_dirown
              l_tngasset

. estat endog
Tests of endogeneity
Ho: variables are exogenous
Durbin (score) chi2(1) = .039507 (p = 0.8424)
Wu-Hausman F(1,314) = .036171 (p = 0.8493)

. estat overid
Tests of overidentifying restrictions:
Sargan (score) chi2(1) = 1.67571 (p = 0.1955)
Basmann chi2(1) = 1.54156 (p = 0.2144)

```

NDIR

First-stage regressions

						Number of obs = 343
						F(28, 314) = 11.36
						Prob > F = 0.0000
						R-squared = 0.5032
						Adj R-squared = 0.4589
						Root MSE = 1.5747
ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
cla	-.451347	.2457498	-1.84	0.067	-.9348715	.0321775
ebit	-.016558	.3191148	-0.05	0.959	-.6444316	.6113156
roe	1.046998	.4485919	2.33	0.020	.1643722	1.929624
tla	-.0111866	.1073245	-0.10	0.917	-.2223527	.1999796
lta	-.5937562	.302613	-1.96	0.051	-1.189162	.0016493
cle	-.5404065	.2064834	-2.62	0.009	-.9466725	-.1341406
lqt	-.077742	.1077475	-0.72	0.471	-.2897404	.1342564
wct	.2330514	.2343704	0.99	0.321	-.2280835	.6941863
nwc	-2.50e-06	.0003396	-0.01	0.994	-.0006707	.0006657
ast	.0693255	.086073	0.81	0.421	-.1000272	.2386783
exp	-.4827057	.285872	-1.69	0.092	-1.045173	.0797612
logta	.0718456	.0532058	1.35	0.178	-.0328393	.1765306
logcap	.225042	.0575575	3.91	0.000	.1117948	.3382892
gdp	-.0319098	.1890491	-0.17	0.866	-.403873	.3400535
blr	.4785262	1.270459	0.38	0.707	-2.021162	2.978215
cpi	.2230676	.231123	0.97	0.335	-.2316778	.6778131
empy	9.749929	18.05554	0.54	0.590	-25.7752	45.27506
age	.0150116	.0096014	1.56	0.119	-.0038795	.0339028
blc	-.4064404	.1945917	-2.09	0.038	-.7893088	-.0235719
gender	-.1299478	.268593	-0.48	0.629	-.6584175	.3985218
cont	-.7473261	.2253701	-3.32	0.001	-1.190753	-.3038998
mdd	-.0747816	.2025799	-0.37	0.712	-.4733673	.323804
ind	2.814986	.3886141	7.24	0.000	2.050369	3.579603
e2	-.0528109	.2577591	-0.20	0.838	-.5599641	.4543424
e3	-.5057584	.2798226	-1.81	0.072	-1.056323	.0448059
e4	-.587649	.2675984	-2.20	0.029	-1.114162	-.0611363
l_ind_ndir	-.143827	.4425389	-0.33	0.745	-1.014543	.7268895
l_tngasset	.1281461	.1201506	1.07	0.287	-.1082559	.3645482
_cons	-1.79875	1.797332	-1.00	0.318	-5.335086	1.737585

Instrumental variables (2SLS) regression

```

Number of obs = 343
Wald chi2(27) = 629.49
Prob > chi2 = 0.0000
R-squared = 0.6348
Root MSE = .30218

```

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ndir	-.093649	.1756131	-0.53	0.594	-.4378444	.2505463
cla	-.0003469	.0963099	-0.00	0.997	-.1891109	.1884171

```

      ebit | -.3274826   .0609676   -5.37   0.000   -.4469769   -.2079883
      roe |  .0650924   .2023858    0.32   0.748   -.3315765   .4617612
      tla |  .0861132   .020527    4.20   0.000   -.045881    .1263453
      lta |  .1153399   .1157052    1.00   0.319   -.1114382   .342118
      cle | -.043263    .1005567   -0.43   0.667   -.2403505   .1538245
      lqt | -.0644407   .0249317   -2.58   0.010   -.1133059   -.0155754
      wct |  .0277236   .0611378    0.45   0.650   -.0921043   .1475515
      nwc | -.0000601   .0000652   -0.92   0.357   -.0001878   .0000677
      ast | -.0224309   .0208347   -1.08   0.282   -.0632663   .0184044
      exp |  .061037    .0957352    0.64   0.524   -.1266006   .2486746
      logta | .0425302   .0164696    2.58   0.010   -.0102504   .0748101
      logcap | -.0040887   .0413329   -0.10   0.921   -.0850996   .0769222
      gdp |  .0514717   .0368287    1.40   0.162   -.0207111   .1236546
      blr | -.1437725   .2575721   -0.56   0.577   -.6486045   .3610595
      cpi |  .0028662   .0569538    0.05   0.960   -.1087613   .1144937
      empy |  4.101027   3.714888    1.10   0.270   -3.18002    11.38207
      age | -.0081127   .0031708   -2.56   0.011   -.0143274   -.001898
      blc | -.1623765   .0777823   -2.09   0.037   -.3148269   -.009926
      gender | -.0236613   .0546227   -0.43   0.665   -.1307199   .0833973
      cont |  .0284744   .136486     0.21   0.835   -.2390332   .2959821
      mdd | -.0301597   .0410403   -0.73   0.462   -.1105972   .0502779
      ind | -.0254151   .5006992   -0.05   0.960   -1.006767   .9559374
      e1 |  .0253442   .1119888    0.23   0.821   -.1941498   .2448382
      e2 |  .0403499   .1046038    0.39   0.700   -.1646697   .2453695
      e3 | -.0346209   .0500783   -0.69   0.489   -.1327725   .0635307
      _cons | .7615508   .5898005    1.29   0.197   -.394437    1.917539

```

```

-----
Instrumented:  ndir
Instruments:   cla ebit roe tla lta cle lqt wct nwc ast exp logta logcap gdp
               blr cpi empy age blc gender cont mdd ind e1 e2 e3 l_ind_ndir
               l_tngasset

```

```

. estat endog
  Tests of endogeneity
  Ho: variables are exogenous
  Durbin (score) chi2(1) = .167234 (p = 0.6826)
  Wu-Hausman F(1,314) = .153169 (p = 0.6958)

. estat overid
  Tests of overidentifying restrictions:
  Sargan (score) chi2(1) = 4.95137 (p = 0.0261)
  Basman chi2(1) = 4.59913 (p = 0.0320)

```

IND

First-stage regressions

					Number of obs	=	343
					F(28, 314)	=	5.72
					Prob > F	=	0.0000
					R-squared	=	0.3377
					Adj R-squared	=	0.2786
					Root MSE	=	0.2117

ind		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

cla		.0432024	.0330805	1.31	0.193	-.0218851	.10829
ebit		.0440404	.0428138	1.03	0.304	-.0401978	.1282786
roe		-.0154838	.0609289	-0.25	0.800	-.1353643	.1043967
tla		-.0125377	.0143858	-0.87	0.384	-.0408424	.015767
lta		.0034211	.0407454	0.08	0.933	-.0767474	.0835896
cle		.0142081	.0280613	0.51	0.613	-.0410039	.0694201
lqt		.0015594	.0144626	0.11	0.914	-.0268966	.0300153
wct		.0199678	.0313734	0.64	0.525	-.0417608	.0816964
nwc		-.0000598	.0000455	-1.31	0.190	-.0001494	.0000298
ast		-.0055565	.011611	-0.48	0.633	-.0284016	.0172886
exp		-.0516221	.0384925	-1.34	0.181	-.1273579	.0241137
logta		.0029963	.0071543	0.42	0.676	-.0110801	.0170727
logcap		.0127348	.0078684	1.62	0.107	-.0027466	.0282162
gdp		-.041154	.0252801	-1.63	0.105	-.0908937	.0085858
blr		.2420704	.1703254	1.42	0.156	-.093053	.5771938
cpi		.0027836	.0311	0.09	0.929	-.0584071	.0639742
empy		-1.989313	2.410383	-0.83	0.410	-6.731857	2.753231
age		.001041	.0012838	0.81	0.418	-.0014849	.0035668
blc		.0642267	.0261096	2.46	0.014	.0128548	.1155986
gender		-.0031557	.035831	-0.09	0.930	-.0736549	.0673435
cont		.0456958	.0308166	1.48	0.139	-.0149373	.106329

mdd		-.0065295	.0272479	-0.24	0.811	-.0601411	.047082
ndir		.0508894	.0070283	7.24	0.000	.0370608	.064718
e2		-.0408483	.0345064	-1.18	0.237	-.1087413	.0270447
e3		-.0309227	.0378113	-0.82	0.414	-.1053182	.0434729
e4		-.0340908	.0361786	-0.94	0.347	-.1052739	.0370924
l_ind_ind		-.0026873	.0261524	-0.10	0.918	-.0541433	.0487687
l_tngasset		-.0039854	.0161926	-0.25	0.806	-.0358452	.0278743
_cons		-.1468483	.2332402	-0.63	0.529	-.6057595	.3120628

Instrumental variables (2SLS) regression

Number of obs = 343
Wald chi2(27) = 14.48
Prob > chi2 = 0.9761
R-squared = .
Root MSE = 1.9948

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
ind		9.532007	36.4113	0.26	0.793	-61.83282 80.89684
cla		-.3924942	1.615661	-0.24	0.808	-3.559132 2.774143
ebit		-.752189	1.636233	-0.46	0.646	-3.959147 2.454769
roe		.1503486	.8159133	0.18	0.854	-1.448812 1.749509
tla		.20992	.4811611	0.44	0.663	-.7331385 1.152978
lta		.1246544	.3986925	0.31	0.755	-.6567685 .9060772
cle		-.1427647	.56913	-0.25	0.802	-1.258239 .9727096
lqt		-.0766639	.151031	-0.51	0.612	-.3726792 .2193514
wct		-.1763055	.7611596	-0.23	0.817	-1.668151 1.31554
nwc		.0005218	.0022134	0.24	0.814	-.0038164 .00486
ast		.0287462	.2360973	0.12	0.903	-.4339961 .4914885
exp		.6050428	1.952539	0.31	0.757	-3.221863 4.431948
logta		.0075889	.1304779	0.06	0.954	-.2481432 .2633209
logcap		-.1428301	.4669783	-0.31	0.760	-1.058091 .7724305
gdp		.4542345	1.513868	0.30	0.764	-2.512892 3.421361
blr		-2.529422	8.93693	-0.28	0.777	-20.04548 14.98664
cpi		-.0432775	.316316	-0.14	0.891	-.6632454 .5766904
empy		22.57494	74.56149	0.30	0.762	-123.5629 168.7128
age		-.0191457	.0393878	-0.49	0.627	-.0963444 .0580529
blc		-.7557559	2.32746	-0.32	0.745	-5.317494 3.805983
gender		.0193071	.3607577	0.05	0.957	-.687765 .7263792
cont		-.3611382	1.666449	-0.22	0.828	-3.627317 2.905041
mdd		.0365137	.3445287	0.11	0.916	-.6387502 .7117777
ndir		-.5209426	1.84936	-0.28	0.778	-4.145622 3.103736
e1		-.3524344	1.312889	-0.27	0.788	-2.925649 2.22078
e2		.0674132	.3961546	0.17	0.865	-.7090356 .8438619
e3		-.068972	.3322328	-0.21	0.836	-.7201363 .5821922
_cons		2.603183	6.524801	0.40	0.690	-10.18519 15.39156

Instrumented: ind

Instruments: cla ebit roe tla lta cle lqt wct nwc ast exp logta logcap gdp
blr cpi empy age blc gender cont mdd ndir e1 e2 e3 l_ind_ind
l_tngasset

estat endog

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 3.5244 (p = 0.1095)

Wu-Hausman F(1,314) = 3.25991 (p = 0.1120)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .050947 (p = 0.8214)

Basman chi2(1) = .046647 (p = 0.8290)

APPENDIX 5b: 2-year Prior To bankruptcy sample endogeneity test

Model 2

MDD

First-stage regressions

						Number of obs = 172
						F(13, 158) = 2.36
						Prob > F = 0.0067
						R-squared = 0.1623
						Adj R-squared = 0.0934
						Root MSE = 0.4167
mdd	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
gdp	.0097721	.0706044	0.14	0.890	-.1296782	.1492223
blr	.7365044	.4621652	1.59	0.113	-.1763144	1.649323
cpi	.048355	.0873706	0.55	0.581	-.1242099	.2209199
empy	3.349354	6.929074	0.48	0.629	-10.33621	17.03491
gender	-.1352723	.0840858	-1.61	0.110	-.3013495	.030805
ind	.0922739	.1266218	0.73	0.467	-.1578159	.3423636
cont	-.1654235	.0767093	-2.16	0.033	-.3169315	-.0139156
ndir	-.0850186	.026336	-3.23	0.002	-.1370347	-.0330025
e2	.2481014	.0969759	2.56	0.011	.0565651	.4396377
e3	-.0300054	.0949799	-0.32	0.752	-.2175993	.1575886
e4	.1486334	.092294	1.61	0.109	-.0336558	.3309226
l_dirown	.011732	.0522327	0.22	0.823	-.0914323	.1148964
l_tngasset	-.0382565	.0449202	-0.85	0.396	-.1269781	.0504651
_cons	.5495797	.1478422	3.72	0.000	.2575777	.8415817

Instrumental variables (2SLS) regression

Number of obs = 172
Wald chi2(12) = 22.08
Prob > chi2 = 0.0366
R-squared = .
Root MSE = 1.0911

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
mdd	-2.627536	2.942189	-0.89	0.372	-8.39412	3.139048
gdp	.0541579	.1900466	0.28	0.776	-.3183266	.4266424
blr	2.09693	2.321073	0.90	0.366	-2.452289	6.646149
cpi	.2111984	.2748685	0.77	0.442	-.3275339	.7499307
empy	14.36424	19.96558	0.72	0.472	-24.76758	53.49606
gender	-.1759258	.4709876	-0.37	0.709	-1.099045	.747193
ind	.0669044	.4206733	0.16	0.874	-.7576001	.8914089
cont	.0925386	.5091745	0.18	0.856	-.9054251	1.090502
ndir	-.33062	.2543639	-1.30	0.194	-.8291641	.167924
e2	.6107458	.7569252	0.81	0.420	-.8728002	2.094292
e3	-.1394651	.2667797	-0.52	0.601	-.6623438	.3834136
e4	.2993123	.48687	0.61	0.539	-.6549354	1.25356
_cons	2.011746	1.743747	1.15	0.249	-1.405935	5.429428

Instrumented: mdd

Instruments: gdp blr cpi empy gender ind cont ndir e2 e3 e4 l_dirown
l_tngasset

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 1.94121 (p = 0.3265)

Wu-Hausman F(1,158) = 1.56849 (p = 0.3438)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .235897 (p = 0.6272)

Basman chi2(1) = .216994 (p = 0.6413)

NDIR

First-stage regressions

reg ndir cont gender ind mdd e2 e3 e4 gdp blr cpi empy l_ind_ndir

Source	SS	df	MS	Number of obs =	172
Model	54.1709096	12	4.51424247	F(12, 159) =	3.04
Residual	236.340718	159	1.48641961	Prob > F =	0.0007
				R-squared =	0.1865
				Adj R-squared =	0.1251
Total	290.511628	171	1.69889841	Root MSE =	1.2192

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
cont	-.8040224	.2188231	-3.67	0.000	-1.236197	-.3718476
gender	-.3698434	.2427609	-1.52	0.130	-.8492952	.1096084
ind	.2393239	.3706654	0.65	0.519	-.4927387	.9713866
mdd	-.7240384	.225753	-3.21	0.002	-1.1699	-.2781772
e2	.5714884	.2841636	2.01	0.046	.0102664	1.13271
e3	.1682294	.2756152	0.61	0.542	-.3761095	.7125683
e4	.3479462	.2677368	1.30	0.196	-.1808331	.8767254
gdp	.0210304	.207939	0.10	0.920	-.3896484	.4317091
blr	.6519877	1.345926	0.48	0.629	-2.00621	3.310186
cpi	.1548412	.2552135	0.61	0.545	-.3492045	.658887
empty	8.709397	20.25466	0.43	0.668	-31.29348	48.71227
l_ind_ndir	.2671658	.4723794	0.57	0.023	-.6657817	1.200113
_cons	3.140247	.6926561	4.53	0.000	1.772254	4.50824

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 8.57894 (p = 0.0034)

Wu-Hausman F(1,158) = 8.29436 (p = 0.0045)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .000064 (p = 0.9936)

Basman chi2(1) = .000058 (p = 0.9939)

Tests of endogeneity

Ho: variables are exogenous

IND

First-stage regressions

. reg ind cont gender ndir mdd e2 e3 e4 gdp blr cpi empty l_ind_ind

Source	SS	df	MS	Number of obs =	172
Model	1.17559067	12	.097965889	F(12, 159) =	1.43
Residual	10.8594742	159	.06829858	Prob > F =	0.1554
				R-squared =	0.0977
				Adj R-squared =	0.0296
Total	12.0350649	171	.070380496	Root MSE =	.26134

ind	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
cont	.0551221	.0483753	1.14	0.256	-.040419	.1506632
gender	-.1270183	.0515299	-2.46	0.015	-.2287897	-.025247
ndir	.011843	.0169565	0.70	0.486	-.021646	.0453321
mdd	.0356219	.04973	0.72	0.475	-.0625945	.1338384
e2	.000949	.0618366	0.02	0.988	-.1211781	.1230762
e3	-.0189224	.0600312	-0.32	0.753	-.1374837	.0996389
e4	.0227783	.0586406	0.39	0.698	-.0930368	.1385933
gdp	-.0108077	.0440813	-0.25	0.807	-.0978682	.0762527

blr		.7048354	.2831441	2.49	0.014	.1456269	1.264044
cpi		-.0270544	.0546914	-0.49	0.622	-.1350698	.080961
empy		-2.194615	4.385827	-0.50	0.617	-10.85661	6.467377
l_ind_ind		.0201621	.0492435	0.41	0.000	-.0770935	.1174178
_cons		.3656011	.0959078	3.81	0.000	.1761835	.5550187

. predict indH
(option xb assumed; fitted values)

Durbin (score) chi2(1) = 8.17634 (p = 0.0042)
Wu-Hausman F(1,158) = 7.88569 (p = 0.0056)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .019438 (p = 0.8891)
Basman chi2(1) = .017858 (p = 0.8937)

Second Stage

. logit status gender cont mdd ndirH indH e2 e3 e4 gdp blr cpi empy

Iteration 0: log likelihood = -119.22132
 Iteration 1: log likelihood = -57.208871
 Iteration 2: log likelihood = -52.055693
 Iteration 3: log likelihood = -51.855127
 Iteration 4: log likelihood = -51.854895
 Iteration 5: log likelihood = -51.854895

Logistic regression	Number of obs	=	172
	LR chi2(12)	=	134.73
	Prob > chi2	=	0.0000
Log likelihood = -51.854895	Pseudo R2	=	0.5651

	status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender		-9.955021	2.832503	-3.51	0.000	-15.50663 -4.403418
cont		1.332529	2.748574	0.48	0.028	-4.054578 6.719636
mdd		-3.485556	2.423168	-1.44	0.150	-8.234878 1.263767
ndirH		-8.226973	3.359226	-2.45	0.014	-14.81093 -1.643012
indH		-75.03214	19.825	-3.78	0.000	-113.8884 -36.17586
e2		4.00987	2.056739	1.95	0.051	-.0212646 8.041005
e3		-1.438571	1.080763	-1.33	0.183	-3.556828 .6796861
e4		3.179257	1.472229	2.16	0.031	.2937414 6.064773
gdp		-.6865821	.6713821	-1.02	0.306	-2.002467 .6293026
blr		63.48975	15.28074	4.15	0.000	33.54005 93.43944
cpi		.3545409	1.035092	0.34	0.732	-1.674202 2.383284
empy		46.90722	76.63331	0.61	0.540	-103.2913 197.1058
_cons		54.02247	14.56444	3.71	0.000	25.47669 82.56826

Model 3

NDIR

First-stage regressions

reg ndir ind gender cont mdd age blc lgta lgcap tla lta cla cle lqt exp ebit roe wct
 nwc ast gdp blr cpi empy e2 e3 e4 l_ind_ndir

Source		SS	df	MS	Number of obs	=	172
Model		91.7642712	27	3.39867671	F(27, 144)	=	2.46
Residual		198.747357	144	1.38018998	Prob > F	=	0.0003
					R-squared	=	0.3159

```
-----+-----
Total | 290.511628 171 1.69889841
Adj R-squared = 0.1876
Root MSE = 1.1748
```

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ind	.0473483	.3710926	0.13	0.899	-.6861442	.7808407
gender	-.2388174	.249503	-0.96	0.340	-.7319789	.254344
cont	-.6271469	.226581	-2.77	0.006	-1.075001	-.1792924
mdd	-.6170573	.2344296	-2.63	0.009	-1.080425	-.1536897
age	.0268051	.0152852	1.75	0.082	-.0034072	.0570175
blc	-.0126748	.2043863	-0.06	0.951	-.4166597	.3913101
lgta	.0854205	.0886315	0.96	0.337	-.0897663	.2606073
lgcap	.0308863	.0680157	0.45	0.650	-.1035518	.1653243
tla	-.0953145	.0701342	-1.36	0.176	-.23394	.0433109
lta	.2041858	.4405157	0.46	0.644	-.6665266	1.074898
cla	-1.659057	.6228268	-2.66	0.009	-2.890121	-.4279932
cle	-.1630802	.1509388	-1.08	0.282	-.4614221	.1352617
lqt	.0065634	.0209523	0.31	0.755	-.0348503	.0479772
exp	-.0412292	.1005141	-0.41	0.682	-.2399028	.1574444
ebit	-.0007055	.2686716	-0.00	0.998	-.5317551	.5303441
roe	.0715166	.0489082	1.46	0.146	-.0251542	.1681873
wct	.0228403	.1621174	0.14	0.888	-.2975969	.3432775
nwc	.0000871	.0004071	0.21	0.831	-.0007176	.0008918
ast	-.013072	.0857089	-0.15	0.879	-.182482	.1563381
gdp	.0181882	.2097413	0.09	0.931	-.3963812	.4327577
blr	1.287676	1.355932	0.95	0.344	-1.392427	3.967778
cpi	.0075111	.2600863	0.03	0.977	-.506569	.5215912
empy	-6.566368	20.69274	-0.32	0.751	-47.46713	34.33439
e2	.5105374	.2927574	1.74	0.083	-.0681195	1.089194
e3	-.0039722	.3037793	-0.01	0.990	-.6044148	.5964705
e4	.2713244	.2779991	0.98	0.331	-.2781618	.8208105
l_ind_ndir	.1887263	.4718966	0.40	0.034	-.7440127	1.121465
_cons	2.377223	1.898844	1.25	0.213	-1.375984	6.130431

```
estat endog
```

```
Tests of endogeneity
Ho: variables are exogenous
```

```
Durbin (score) chi2(1) = 6.74086 (p = 0.0094)
Wu-Hausman F(1,143) = 5.83291 (p = 0.0170)
```

```
. estat overid
```

```
Tests of overidentifying restrictions:
```

```
Sargan (score) chi2(1) = 2.6e-06 (p = 0.9987)
Basman chi2(1) = 2.2e-06 (p = 0.9988)
```

Second Stages

```
logit status ndirHH ind gender cont mdd age blc lgta lgcap tla lta cle lqt exp ebit
roe wct nwc ast cpi empy
```

```
Iteration 0: log likelihood = -119.22132
Iteration 1: log likelihood = -34.031566
Iteration 2: log likelihood = -25.078524
Iteration 3: log likelihood = -20.575117
Iteration 4: log likelihood = -20.100203
Iteration 5: log likelihood = -20.072204
Iteration 6: log likelihood = -20.072156
Iteration 7: log likelihood = -20.072156
```

```
Logistic regression
Number of obs = 172
LR chi2(21) = 198.30
Prob > chi2 = 0.0000
Pseudo R2 = 0.8316
```

```
Log likelihood = -20.072156
```

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
--------	-------	-----------	---	------	----------------------	--

ndirHH		-3.376513	2.083294	-1.62	0.100	-7.459694	.7066684
ind		-4.522221	2.293727	-1.97	0.049	-9.017843	-.0265995
gender		1.449645	1.467242	0.99	0.323	-1.426097	4.325387
cont		5.883446	2.151083	2.74	0.006	1.667402	10.09949
mdd		-.8891331	1.576633	-0.56	0.573	-3.979276	2.20101
age		-.247277	.1190934	-2.08	0.038	-.4806958	-.0138581
blc		-5.609227	2.334131	-2.40	0.016	-10.18404	-1.034415
lgt		.7893906	.6274754	1.26	0.208	-.4404386	2.01922
lgcap		1.118271	.5203614	2.15	0.032	.098381	2.13816
tla		1.250951	.6125791	2.04	0.041	.0503178	2.451584
lta		-2.9094	3.729673	-0.78	0.435	-10.21942	4.400625
cle		.7342066	.6145549	1.19	0.232	-.470299	1.938712
lqt		-.1682998	.2453409	-0.69	0.493	-.6491592	.3125595
exp		.0967403	.5388151	0.18	0.858	-.959318	1.152799
ebit		-18.28706	7.257272	-2.52	0.012	-32.51105	-4.063064
roe		.5389129	.5281287	1.02	0.308	-.4962004	1.574026
wct		-4.026473	2.117478	-1.90	0.057	-8.176654	.1237083
nwc		.0012589	.0026746	0.47	0.638	-.0039832	.0065011
ast		-.3033151	.5803786	-0.52	0.601	-1.440836	.834206
cpi		3.416191	1.883828	1.81	0.020	-.2760431	7.108426
empy		154.109	186.94	0.82	0.410	-212.2867	520.5047
_cons		-16.08512	13.15313	-1.22	0.221	-41.86478	9.694532

Note: 7 failures and 10 successes completely determined.

MDD

First-stage regressions

						Number of obs	=	172
						F(28, 143)	=	1.80
						Prob > F	=	0.0137
						R-squared	=	0.2609
						Adj R-squared	=	0.1162
						Root MSE	=	0.4114
mdd		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]		
ind		.1010247	.1302561	0.78	0.439	-.1564516	.358501	
gender		-.0978729	.0882751	-1.11	0.269	-.2723655	.0766198	
cont		-.0893554	.0814495	-1.10	0.274	-.2503561	.0716453	
ndir		-.0746005	.028534	-2.61	0.010	-.1310034	-.0181975	
age		.0044653	.0054108	0.83	0.411	-.0062301	.0151608	
blc		-.0414909	.0713674	-0.58	0.562	-.1825622	.0995805	
lgt		-.0721857	.0307905	-2.34	0.020	-.1330491	-.0113223	
lgcap		.000608	.0239625	0.03	0.980	-.0467584	.0479745	
tla		-.0644863	.0245443	-2.63	0.010	-.1130029	-.0159697	
lta		.0328129	.1549287	0.21	0.833	-.2734335	.3390593	
cla		.2498038	.2222571	1.12	0.263	-.18953	.6891376	
cle		-.0139	.0541145	-0.26	0.798	-.1208676	.0930677	
lqt		-.0114779	.007419	-1.55	0.124	-.0261431	.0031872	
exp		-.0042897	.0348468	-0.12	0.902	-.0731712	.0645917	
ebit		.1693781	.0944453	1.79	0.075	-.0173113	.3560675	
roe		.0034294	.0173045	0.20	0.843	-.0307763	.0376351	
wct		-.0181014	.0567446	-0.32	0.750	-.130268	.0940651	
nwc		-.0000849	.0001429	-0.59	0.553	-.0003674	.0001976	
ast		.001272	.0299499	0.04	0.966	-.0579297	.0604738	
gdp		-.0022244	.0726013	-0.03	0.976	-.1457348	.1412861	
blr		.4362881	.4777382	0.91	0.363	-.5080533	1.380629	
cpi		.0237871	.0910759	0.26	0.794	-.1562419	.2038162	
empy		.4903101	7.25809	0.07	0.946	-13.8567	14.83732	
e2		.1669287	.1029839	1.62	0.107	-.0366388	.3704963	
e3		-.102878	.1061893	-0.97	0.334	-.3127815	.1070255	
e4		.0664346	.0984987	0.67	0.501	-.128267	.2611363	
l_dirown		-.0089146	.0556507	-0.16	0.873	-.1189189	.1010897	
l_tngasset		-.0213923	.0471105	-0.45	0.650	-.1145154	.0717307	
_cons		1.679307	.6200101	2.71	0.008	.4537382	2.904876	

Instrumental variables (2SLS) regression

Number of obs = 172
Wald chi2(27) = 50.73
Prob > chi2 = 0.0037
R-squared = 0.2569
Root MSE = .78291

ast		.0132371	.0191593	0.69	0.491	-.024635	.0511092
gdp		-.0153723	.0464707	-0.33	0.741	-.1072306	.0764861
blr		.716959	.3012271	2.38	0.019	.1215258	1.312392
cpi		-.0402727	.0580406	-0.69	0.489	-.1550011	.0744556
empy		-2.283117	4.74495	-0.48	0.631	-11.66242	7.096188
e2		-.0132028	.0670738	-0.20	0.844	-.1457871	.1193815
e3		-.0456779	.0691759	-0.66	0.510	-.1824174	.0910617
e4		.006893	.063753	0.11	0.914	-.1191271	.1329131
l_ind_ind		-.016106	.0541104	-0.30	0.766	-.1230657	.0908537
l_tngasset		.0415161	.0300154	1.38	0.169	-.0178151	.1008472
_cons		.2377752	.40836	0.58	0.561	-.5694268	1.044977

Instrumental variables (2SLS) regression

Number of obs = 172
Wald chi2(27) = 185.75
Prob > chi2 = 0.0000
R-squared = 0.3313
Root MSE = .40886

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
ind		1.189222	1.100959	1.08	0.280	-.9686192 3.347062
mdd		-.0331153	.0933004	-0.35	0.723	-.2159808 .1497502
gender		.2302976	.1421773	1.62	0.105	-.0483648 .50896
cont		.3238139	.1033481	3.13	0.002	.1212554 .5263725
ndir		-.0938767	.0291669	-3.22	0.001	-.1510428 -.0367106
age		-.0135431	.0054886	-2.47	0.014	-.0243006 -.0027856
blc		-.0714583	.0896913	-0.80	0.426	-.2472501 .1043334
lgta		-.028081	.0405461	-0.69	0.489	-.10755 .0513879
lgcap		.0840787	.0323136	2.60	0.009	.0207453 .1474122
tla		.0056794	.0316608	0.18	0.858	-.0563747 .0677335
lta		.0190166	.155385	0.12	0.903	-.2855324 .3235656
cla		.2053829	.2510817	0.82	0.413	-.2867282 .697494
cle		.1020087	.0813623	1.25	0.210	-.0574585 .2614759
lqt		-.0106115	.007886	-1.35	0.178	-.0260677 .0048448
exp		.0153704	.0360022	0.43	0.669	-.0551927 .0859335
ebit		-.109345	.0963571	-1.13	0.256	-.2982015 .0795115
roe		.0045045	.0178876	0.25	0.801	-.0305545 .0395635
wct		-.1071141	.0561826	-1.91	0.057	-.21723 .0030018
nwc		-.0001828	.0001585	-1.15	0.249	-.0004936 .0001279
ast		-.0442931	.032408	-1.37	0.172	-.1078116 .0192254
gdp		.0203	.0752027	0.27	0.787	-.1270945 .1676946
blr		-1.009204	.9717856	-1.04	0.299	-2.913869 .8954603
cpi		.1737802	.1020849	1.70	0.089	-.0263025 .3738629
empy		12.37767	7.540765	1.64	0.101	-2.401954 27.1573
e1		.1011328	.0989458	1.02	0.307	-.0927974 .2950629
e2		.1119132	.0958875	1.17	0.243	-.0760227 .2998492
e3		.1136358	.1096933	1.04	0.300	-.1013592 .3286309
_cons		-.2448581	.6732858	-0.36	0.716	-1.564474 1.074758

Instrumented: ind

Instruments: mdd gender cont ndir age blc lgta lgcap tla lta cla cle lqt
exp ebit roe wct nwc ast gdp blr cpi empy e1 e2 e3 l_ind_ind
l_tngasset

. estat endog

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .310872 (p = 0.2689)

Wu-Hausman F(1,143) = .802481 (p = 0.3962)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) cshi2(1) = .938744 (p = 0.3326)

Basman chi2(1) = .78475 (p = 0.3757)

APPENDIX 5c: 1-year Prior To bankruptcy sample endogeneity test

Model 2

IND

First-stage regressions

```
reg ind gender cont ndir mdd e2 e3 e4 gdp blr cpi empy l_ind_ind
```

Source	SS	df	MS	Number of obs	=	116
Model	.611620437	12	.05096837	F(12, 103)	=	1.38
Residual	3.79994687	103	.036892688	Prob > F	=	0.0867
				R-squared	=	0.1386
				Adj R-squared	=	0.0383
Total	4.41156731	115	.038361455	Root MSE	=	.19207

ind	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	.052607	.0384917	1.37	0.175	-.0237322 .1289462
cont	-.0983861	.0376646	-2.61	0.010	-.173085 -.0236871
ndir	.0069716	.0120259	0.58	0.563	-.0168789 .0308222
mdd	.0433233	.0432661	1.00	0.319	-.0424848 .1291314
e2	-.059064	.0582041	-1.01	0.313	-.1744981 .05637
e3	-.0248656	.0583472	-0.43	0.671	-.1405836 .0908524
e4	.0193123	.0547479	0.35	0.725	-.0892672 .1278918
gdp	.0422714	.041376	1.02	0.309	-.0397881 .1243309
blr	-.1123004	.2587739	-0.43	0.665	-.6255174 .4009167
cpi	-.0330065	.0494763	-0.67	0.506	-.1311312 .0651181
empy	-1.015733	4.014616	-0.25	0.801	-8.977777 6.946311
l_ind_ind	-.0236813	.0428667	-0.55	0.023	-.1086972 .0613347
cons	.1254608	.084187	1.49	0.139	-.0415043 .2924259

```
. predict indH
(option xb assumed; fitted values)
```

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 7.62069 (p = 0.0058)
Wu-Hausman F(1,102) = 7.17213 (p = 0.0086)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .067177 (p = 0.7955)
Basman chi2(1) = .059103 (p = 0.8079)

Second Stage

```
. logit status gender cont ndir mdd indH e2 e3 e4 gdp blr cpi empy
```

```
Iteration 0: log likelihood = -80.405073
Iteration 1: log likelihood = -47.064531
Iteration 2: log likelihood = -46.288978
Iteration 3: log likelihood = -46.280264
Iteration 4: log likelihood = -46.280264
```

Logistic regression

Number of obs	=	116
LR chi2(12)	=	68.25
Prob > chi2	=	0.0000
Pseudo R2	=	0.4244

Log likelihood = -46.280264

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender	2.307739	1.552673	1.49	0.137	-.7354432 5.350921
cont	2.475622	2.612993	0.78	0.074	-7.168933 3.07381

ndir		.3856178	.2616875	1.47	0.141	-.1272802	.8985158
mdd		2.336772	1.297455	1.80	0.072	-.2061931	4.879737
indH		-63.49421	28.02215	-2.27	0.023	-118.4166	-8.571804
e2		-5.038569	1.873074	-2.69	0.007	-8.709727	-1.367411
e3		-2.868532	1.220033	-2.35	0.019	-5.259753	-.4773109
e4		.4892466	1.032585	0.47	0.636	-1.534583	2.513076
gdp		3.174249	1.471493	2.16	0.031	.2901757	6.058323
blr		-12.5264	5.171344	-2.42	0.015	-22.66204	-2.390747
cpi		2.62769	1.26995	2.07	0.039	-5.116714	.9386032
empy		-62.83271	72.69987	-0.86	0.387	-205.3218	79.65642
_cons		8.584488	4.284035	2.00	0.045	.1879336	16.98104

MDD

First-stage regressions

Number of obs	=	116
F(13, 102)	=	1.06
Prob > F	=	0.4005
R-squared	=	0.1192
Adj R-squared	=	0.0069
Root MSE	=	0.4334

	mdd	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gdp		-.0845366	.0954509	-0.89	0.378	-.2738631 .1047898
blr		.1963917	.597428	0.33	0.743	-.9886039 1.381387
cpi		-.1072783	.1099019	-0.98	0.331	-.3252681 .1107116
empy		16.38798	8.949738	1.83	0.070	-1.363784 34.13974
gender		-.0440854	.0871488	-0.51	0.614	-.2169446 .1287739
ind		.209702	.2219317	0.94	0.347	-.2304985 .6499024
cont		-.0888901	.0873916	-1.02	0.311	-.262231 .0844507
ndir		-.0531273	.0267266	-1.99	0.050	-.1061393 -.0001153
e2		.0900317	.1319877	0.68	0.497	-.1717654 .3518287
e3		.0067556	.1327609	0.05	0.960	-.256575 .2700861
e4		.1075268	.1234819	0.87	0.386	-.1373989 .3524525
l_dirown		-.0187631	.0743932	-0.25	0.801	-.1663217 .1287954
l_tngasset		-.0809765	.0527826	-1.53	0.128	-.1856705 .0237176
_cons		.3540646	.1687998	2.10	0.038	.019251 .6888783

Instrumental variables (2SLS) regression

Number of obs	=	116
Wald chi2(12)	=	52.22
Prob > chi2	=	0.0000
R-squared	=	.
Root MSE	=	.51233

	status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
mdd		-.9110013	.7662657	-1.19	0.234	-2.412854 .5908518
gdp		-.0173285	.1202393	-0.14	0.885	-.2529932 .2183362
blr		-.4503257	.6980963	-0.65	0.519	-1.818569 .917918
cpi		-.1262342	.1519515	-0.83	0.406	-.4240536 .1715853
empy		15.09175	16.38975	0.92	0.357	-17.03156 47.21506
gender		-.1607749	.1087097	-1.48	0.139	-.373842 .0522921
ind		.1793088	.3089786	0.58	0.562	-.4262782 .7848958
cont		.6087867	.1215885	5.01	0.000	.3704777 .8470958
ndir		-.0563027	.0504272	-1.12	0.264	-.1551383 .0425328
e2		-.0840931	.1715624	-0.49	0.624	-.4203493 .2521631
e3		-.0897151	.1578406	-0.57	0.570	-.3990769 .2196467
e4		.0253144	.1665752	0.15	0.879	-.301167 .3517958
_cons		.6739125	.3842961	1.75	0.079	-.0792941 1.427119

Instrumented: mdd

Instruments: gdp blr cpi empy gender ind cont ndir e2 e3 e4 l_dirown
l_tngasset

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 2.56603 (p = 0.1092)

Wu-Hausman F(1,102) = 2.30738 (p = 0.1319)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = 3.21276 (p = 0.0731)

Basman chi2(1) = 2.90548 (p = 0.0883)

NDIR

First-stage regressions

					Number of obs	=	116
					F(13, 102)	=	0.82
					Prob > F	=	0.6397
					R-squared	=	0.0945
					Adj R-squared	=	-0.0210
					Root MSE	=	1.5770

ndir		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

gdp		.2456004	.3420155	0.72	0.474	-.4327858	.9239866
blr		-1.912558	2.118362	-0.90	0.369	-6.114319	2.289204
cpi		-.0827139	.404793	-0.20	0.838	-.885619	.7201911
empy		14.36693	33.11625	0.43	0.665	-51.319	80.05286
gender		-.4698601	.314269	-1.50	0.138	-1.093211	.1534909
ind		.489395	.8073207	0.61	0.546	-1.111922	2.090712
cont		-.096006	.3244943	-0.30	0.768	-.7396389	.547627
mdd		-.7007466	.3535314	-1.98	0.050	-1.401974	.0004811
e2		.6358385	.4768434	1.33	0.185	-.3099782	1.581655
e3		.3770728	.4810949	0.78	0.435	-.5771767	1.331322
e4		.6637716	.4494448	1.48	0.143	-.2277	1.555243
l_ind_ndir		-.2077155	.7170974	-0.29	0.773	-1.630075	1.214644
l_tngasset		-.1252414	.1936673	-0.65	0.519	-.5093796	.2588968
_cons		3.618492	1.052104	3.44	0.001	1.531649	5.705335

Instrumental variables (2SLS) regression

Number of obs = 116
Wald chi2(12) = 54.78
Prob > chi2 = 0.0000
R-squared = 0.0214
Root MSE = .49462

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ndir	-.235297	.4487692	-0.52	0.600	-1.114869	.6442745
gdp	.0980629	.1613866	0.61	0.543	-.218249	.4143748
blr	-1.036275	1.110946	-0.93	0.351	-3.213689	1.141138
cpi	-.0564218	.1319299	-0.43	0.669	-.3149997	.2021562
empy	4.369425	12.53669	0.35	0.727	-20.20204	28.94089
gender	-.227745	.2350379	-0.97	0.333	-.6884109	.2329208
ind	.1016523	.3350525	0.30	0.762	-.5550385	.7583431
cont	.6661252	.104861	6.35	0.000	.4606013	.871649
mdd	-.1909436	.3191123	-0.60	0.550	-.8163921	.434505
e2	-.0235486	.322794	-0.07	0.942	-.6562132	.6091159
e3	-.0297295	.2421955	-0.12	0.902	-.504424	.4449649
e4	.0778444	.3215312	0.24	0.809	-.5523452	.7080339
_cons	1.064334	1.561898	0.68	0.496	-1.99693	4.125599

Instrumented: ndir

Instruments: gdp blr cpi empy gender ind cont mdd e2 e3 e4 l_ind_ndir
l_tngasset

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = .453053 (p = 0.5009)

Wu-Hausman F(1,102) = .399936 (p = 0.5285)

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = 6.09191 (p = 0.0136)

Basman chi2(1) = 5.65359 (p = 0.0174)

Model 3

NDIR

First-stage regressions

reg ndir gender ind cont mdd age blc lgta lgcapital tla lta cle lqt cla ebit roe wct
nwc ast exp gdp blr cpi empy e2 e3 e4 l_ind_ndir

Source	SS	df	MS	Number of obs =	116
Model	68.5343198	27	2.53830814	F(27, 88) =	1.06
Residual	211.603611	88	2.40458649	Prob > F =	0.4094
				R-squared =	0.2446
				Adj R-squared =	0.0129
Total	280.137931	115	2.43598201	Root MSE =	1.5507

ndir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
gender	-.6357494	.3425962	-1.86	0.067	-1.316587 .0450885
ind	.1359598	.8217554	0.17	0.869	-1.497106 1.769026
cont	-.0942691	.366686	-0.26	0.798	-.8229805 .6344423
mdd	-.3037342	.3678283	-0.83	0.411	-1.034716 .4272472
age	.0108367	.0241622	0.45	0.655	-.0371807 .058854
b1c	.2311211	.3239249	0.71	0.477	-.4126115 .8748536
lgta	.2475904	.1604611	1.54	0.126	-.0712924 .5664731
lgcapital	.0982441	.1384112	0.71	0.480	-.1768192 .3733073
tla	-.0435097	.104557	-0.42	0.678	-.2512947 .1642752
lta	1.001782	.5596076	1.79	0.077	-.1103202 2.113885
cle	-1.132785	1.022678	-1.11	0.271	-3.165144 .8995732
lqt	.0455478	.0430745	1.06	0.293	-.0400536 .1311492
cla	.0787031	.258358	0.30	0.761	-.4347292 .5921353
ebit	-.7786222	.4787815	-1.63	0.101	-1.7301 .1728555
roe	.0409927	.0734146	0.56	0.578	-.1049034 .1868888
wct	-.2089897	.2332404	-0.90	0.373	-.6725059 .2545265
nwc	.0006313	.0006468	0.98	0.332	-.0006541 .0019167
ast	-.1374788	.132115	-1.04	0.301	-.4000297 .125072
exp	.4125854	.9989039	0.41	0.681	-1.572526 2.397697
gdp	.1630788	.3575339	0.46	0.649	-.5474447 .8736024
blr	-1.81447	2.286544	-0.79	0.430	-6.358497 2.729556
cpi	-.155004	.4233401	-0.37	0.715	-.9963035 .6862956
empy	46.86882	35.39728	1.32	0.189	-23.47584 117.2135
e2	.0611438	.5325864	0.11	0.909	-.9972598 1.119547
e3	.0303083	.5415591	0.06	0.955	-1.045927 1.106543
e4	.314313	.5036135	0.62	0.534	-.686513 1.315139
l_ind_ndir	.3101816	.811465	0.38	0.003	-1.302434 1.922798
_cons	-3.113258	2.981156	-1.04	0.299	-9.03768 2.811163

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 5.61249 (p = 0.0178)

Wu-Hausman F(1,87) = 4.42339 (p = 0.0383)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .928021 (p = 0.3354)

Basman chi2(1) = .701629 (p = 0.4022)

Second Stage

Logistic regression	Number of obs =	116
	LR chi2(20) =	130.42
	Prob > chi2 =	0.0000
Log likelihood = -15.195303	Pseudo R2 =	0.8110

status	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
ndirH	-1.213811	1.579589	-0.77	0.042	-4.309749 1.882127
gender	-1.110872	1.534877	-0.72	0.469	-4.119175 1.897431
cont	14.47361	6.690193	2.16	0.031	1.361069 27.58614
mdd	.2452074	2.035821	0.12	0.904	-3.744928 4.235343
age	-.8358893	.3536472	-2.36	0.018	-1.529025 -.1427536


```

      cont | .3392865 .4904354 0.69 0.489 -.6219492 1.300522
      ndir | -.0140267 .0282001 -0.50 0.619 -.0692979 .0412444
      mdd | .0541119 .2367752 0.23 0.819 -.4099518 .5181898
      age | -.0142474 .014366 -0.99 0.321 -.0424043 .0139095
      blc | -.1487266 .0775492 -1.92 0.055 -.3007201 .003267
      lgta | .046387 .047808 0.97 0.332 -.047315 .140089
  lgcapital | -.0181785 .0316325 -0.57 0.566 -.080177 .0438199
      tla | .0267617 .0430256 0.62 0.534 -.057567 .1110904
      lta | .0669384 .1624884 0.41 0.680 -.251533 .3854099
      cle | .1583117 .2453699 0.65 0.519 -.3226044 .6392278
      lqt | -.0005724 .0103851 -0.06 0.956 -.0209269 .0197821
      cla | .0208638 .2968607 0.07 0.944 -.5609725 .6027001
      ebit | -.1149734 .1994246 -0.58 0.564 -.5058383 .2758916
      roe | -.0244939 .0192546 -1.27 0.203 -.0622322 .0132444
      wct | -.0763802 .0880105 -0.87 0.385 -.2488776 .0961172
      nwc | -.0000769 .0002105 -0.37 0.715 -.0004895 .0003357
      ast | -.1062115 .142548 -0.75 0.456 -.3856004 .1731773
      exp | .2915477 .2745339 1.06 0.288 -.2465287 .8296242
      gdp | .0729835 .2287212 0.32 0.750 -.3753018 .5212689
      blr | -1.132654 .5675472 -2.00 0.046 -2.245026 -.020282
      cpi | -.0741979 .3372174 -0.22 0.826 -.735132 .5867361
      empy | -4.905484 8.428631 -0.58 0.561 -21.4253 11.61433
      e1 | .0774528 .1339166 0.58 0.563 -.1850188 .3399244
      e2 | -.118869 .4846573 -0.25 0.806 -1.06878 .8310419
      e3 | -.0512641 .3032167 -0.17 0.866 -.645558 .5430297
      _cons | .1260714 .6440738 0.20 0.845 -1.13629 1.388433

```

```

-----
Instrumented: ind
Instruments: gender cont ndir mdd age blc lgta lgcapital tla lta cle lqt
              cla ebit roe wct nwc ast exp gdp blr cpi empy e1 e2 e3
              l_ind_ind l_tngasset

```

```

. estat endog
  Tests of endogeneity
  Ho: variables are exogenous
  Durbin (score) chi2(1) = .081012 (p = 0.7759)
  Wu-Hausman F(1,87) = .060802 (p = 0.8058)

. estat overid
  Tests of overidentifying restrictions:
  Sargan (score) chi2(1) = 1.89482 (p = 0.1687)
  Basman chi2(1) = 1.44471 (p = 0.2294)

```

MDD

First-stage regressions

```

-----
Number of obs = 116
F( 28, 87) = 0.76
Prob > F = 0.7958
R-squared = 0.1959
Adj R-squared = -0.0629
Root MSE = 0.4484

-----
      mdd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      gender | -.0578125   .1005403    -0.58   0.567    -1.2576471   .1420222
      cont | -.0441192   .1050796    -0.42   0.676    -1.2529762   .1647379
      ndir | -.030315   .0308476    -0.98   0.328    -0.916279   .0309978
      ind | .2185759   .2379243     0.92   0.361    -0.2543245   .6914763
      age | .0002106   .0069711     0.03   0.976    -0.0136453   .0140665
      blc | .0032318   .0945094     0.03   0.973    -0.1846159   .1910794
      lgta | -.0326605   .0468036    -0.70   0.487    -0.1256876   .0603667
  lgcapital | -.015308   .0387962    -0.39   0.694    -0.0924196   .0618037
      tla | -.0359811   .0301792    -1.19   0.236    -0.0959654   .0240033
      lta | -.0957918   .1692568    -0.57   0.573    -0.432208   .2406244
      cle | .3949557   .2960926     1.33   0.186    -0.1935604   .9834717
      lqt | -.0044468   .0124984    -0.36   0.722    -0.02931   .020374
      cla | -.0530292   .0741042    -0.72   0.476    -0.2003193   .094261
      ebit | .1754179   .1358589     1.29   0.200    -0.0946164   .4454522
      roe | .0034256   .0213699     0.16   0.873    -0.0390494   .0459006
      wct | -.0380566   .068025    -0.56   0.577    -0.1732636   .0971503
      nwc | -.0001485   .0001895    -0.78   0.436    -0.0005251   .0002282
      ast | .0176949   .0394772     0.45   0.655    -0.0607703   .09616
      exp | .1608252   .287528     0.56   0.577    -0.4106679   .7323183
      gdp | -.0296986   .1053439    -0.28   0.779    -0.2390811   .1796839
      blr | .0975361   .6769805     0.14   0.886    -1.248036   1.443108

```

cpi		-.0583615	.1212031	-0.48	0.631	-.2992658	.1825428
empy		10.67821	10.27385	1.04	0.302	-9.742185	31.09861
e2		.0989095	.1542589	0.64	0.523	-.2076968	.4055159
e3		-.0092013	.1572552	-0.06	0.953	-.321763	.3033604
e4		.0326236	.1458431	0.22	0.824	-.2572555	.3225026
l_dirown		-.026791	.0823631	-0.33	0.746	-.1904966	.1369146
l_tngasset		-.0709502	.0605815	-1.17	0.245	-.1913624	.0494621
_cons		1.01756	.7746231	1.31	0.192	-.5220878	2.557207

Instrumental variables (2SLS) regression

Number of obs = 116
Wald chi2(27) = 125.12
Prob > chi2 = 0.0000
R-squared = 0.4093
Root MSE = .38429

status		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
mdd		-.6015413	.697744	-0.86	0.389	-1.969094 .7660117
gender		-.1474573	.0944126	-1.56	0.118	-.3325025 .037588
cont		.4309405	.0929413	4.64	0.000	.2487789 .6131021
ind		.1356175	.2510197	0.54	0.589	-.3563721 .627607
ndir		-.0330023	.0321967	-1.03	0.305	-.0961068 .0301021
age		-.0168631	.0059436	-2.84	0.005	-.0285123 -.0052139
b1c		-.1567403	.0807034	-1.94	0.052	-.3149161 .0014354
lgta		.0200792	.0461096	0.44	0.663	-.0702939 .1104523
lgcapital		-.0303992	.0355024	-0.86	0.392	-.0999826 .0391841
tla		.010661	.0380098	0.28	0.779	-.0638369 .0851588
lta		-.0340867	.1683697	-0.20	0.840	-.3640853 .2959119
cle		.4161746	.3892377	1.07	0.285	-.3467173 1.179067
lqt		-.0027806	.0108682	-0.26	0.798	-.0240819 .0185208
cla		-.0748452	.0707108	-1.06	0.290	-.2134358 .0637454
ebit		-.0436043	.1719762	-0.25	0.800	-.3806714 .2934628
roe		-.0259281	.0182243	-1.42	0.155	-.0616471 .0097909
wct		-.0792514	.0617891	-1.28	0.200	-.2003558 .0418531
nwc		-.0001852	.0001819	-1.02	0.309	-.0005417 .0001713
ast		-.0607398	.0361698	-1.68	0.093	-.1316314 .0101517
exp		.4090522	.261289	1.57	0.117	-.1030649 .9211693
gdp		.0200858	.0881808	0.23	0.820	-.1527453 .192917
blr		-1.049883	.5606085	-1.87	0.061	-2.148655 .0488897
cpi		-.0379229	.1129434	-0.34	0.737	-.2592879 .183442
empy		1.219944	11.30466	0.11	0.914	-20.93678 23.37666
e1		.0477747	.125787	0.38	0.704	-.1987632 .2943126
e2		.0323806	.1155437	0.28	0.779	-.1940809 .258842
e3		.0048175	.1074521	0.04	0.964	-.2057847 .2154198
_cons		.8258158	1.017096	0.81	0.417	-1.167656 2.819287

Instrumented: mdd

Instruments: gender cont ind ndir age b1c lgta lgcapital tla lta cle lqt
cla ebit roe wct nwc ast exp gdp blr cpi empy e1 e2 e3
l_dirown l_tngasset

. estat endog

Tests of endogeneity

Ho: variables are exogenous

Durbin (score) chi2(1) = 1.22974 (p = 0.2675)

Wu-Hausman F(1,87) = .932186 (p = 0.3370)

. estat overid

Tests of overidentifying restrictions:

Sargan (score) chi2(1) = 2.69229 (p = 0.1008)

Basman chi2(1) = 2.0672 (p = 0.1505)

APPENDIX 6: Artificial Neural Network for Nigerian Sample

APPENDIX 6a: Model 1 (3-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	11.575
	Percent Incorrect Predictions	4.0%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
Holdout	Training Time	0:00:00.07
	Percent Incorrect Predictions	8.6%

Dependent Variable: Distress Status

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	2.418		
	EBIT	-5.298		
	ROE	.389		
	TLA	4.405		
	LTA	3.372		
	CLE	1.788		
	CLA	.412		
	LQT	-1.298		
	WCT	-.930		
	NWC	-.121		
	AST	-.140		
	EXP	.675		
	LogTA	-1.387		
	LogCAP	.134		
	AGE	-1.926		
	BLC	-1.038		
Hidden Layer 1	(Bias)		1.082	-1.091
	H(1:1)		-5.434	5.529

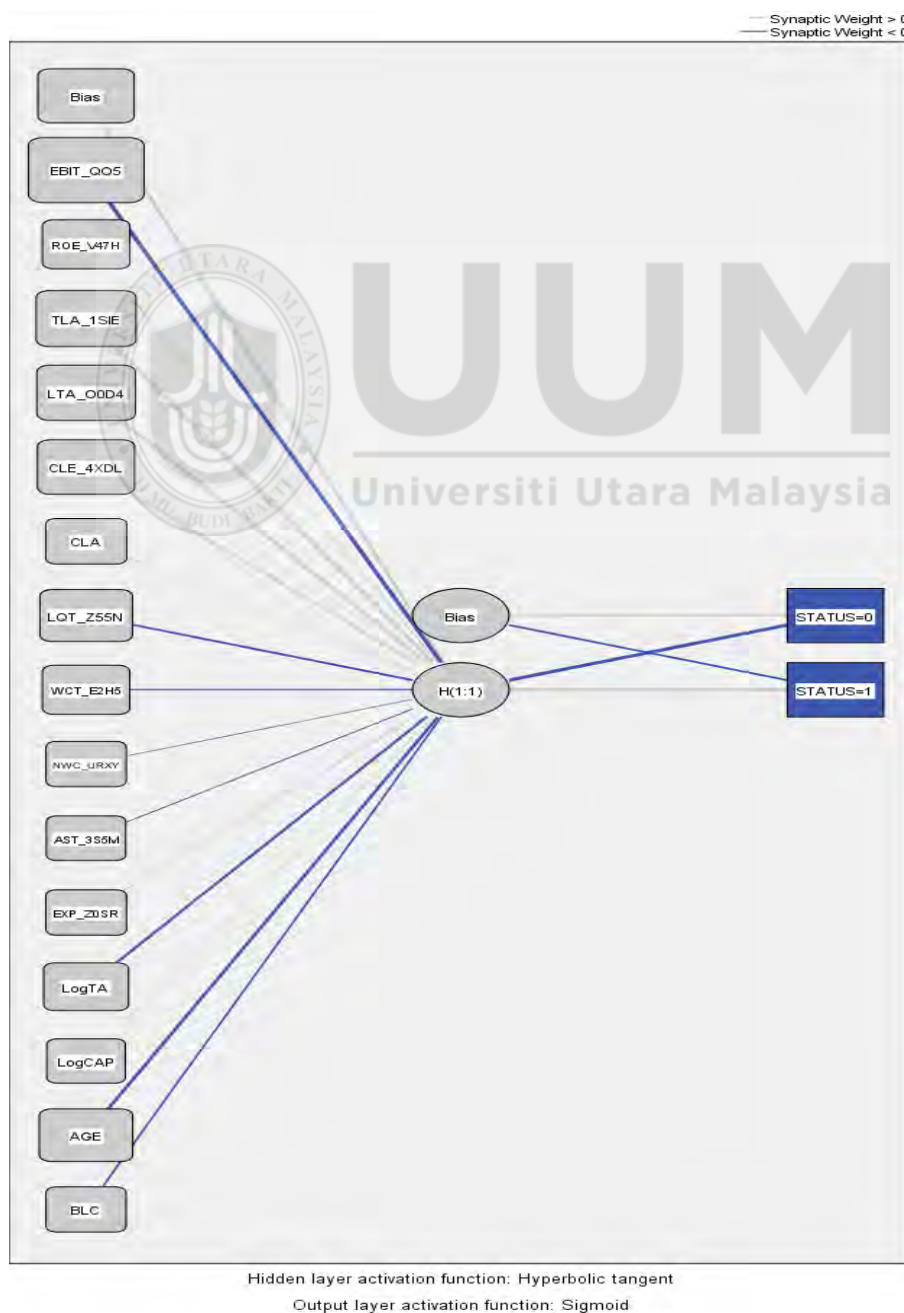
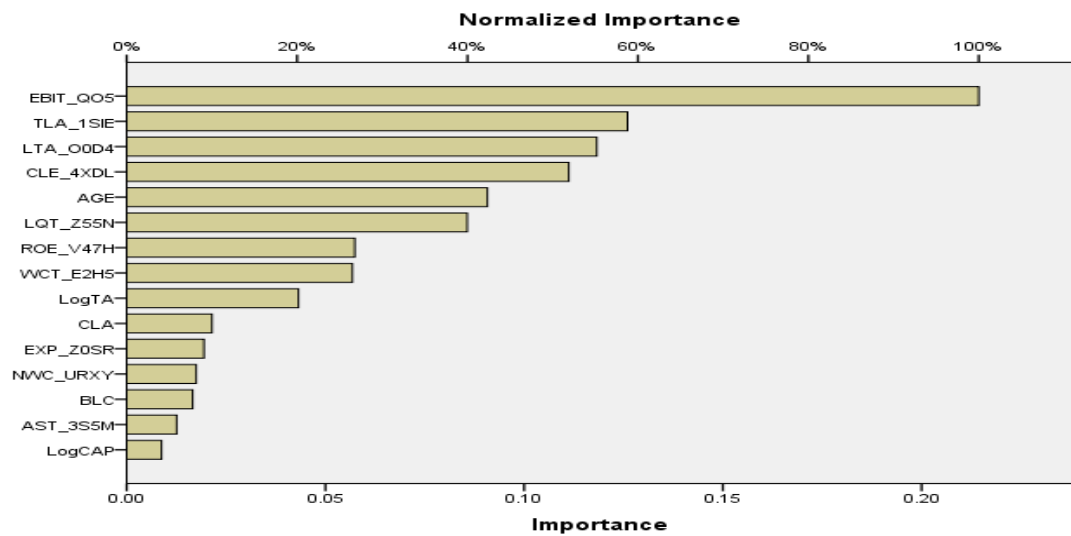
Classification

Sample	Observed	Predicted		
		Non-Failed SME	Failed SME	Percent Correct
Training	Non-Failed SME	128	8	94.1%
	Failed SME	3	134	97.8%
	Overall Percent	48.0%	52.0%	96.0%
	Non-Failed SME	30	5	85.7%
Holdout	Failed SME	1	34	97.1%
	Overall Percent	44.3%	55.7%	91.4%

Dependent Variable: Distress Status

Independent Variable Importance

	Importance	Normalized Importance
EBIT	.214	100.0%
ROE	.057	26.8%
TLA	.126	58.8%
LTA	.118	55.2%
CLE	.111	51.9%
CLA	.021	10.0%
LQT	.086	40.0%
WCT	.057	26.5%
NWC	.017	8.2%
AST	.013	5.9%
EXP	.019	9.1%
LogTA	.043	20.2%
LogCAP	.009	4.1%
AGE	.091	42.3%
BLC	.017	7.8%



APPENDIX 6b: Model 2 (3-year Prior to bankruptcy sample)

Model Summary

Training	Sum of Squares Error	40.910
	Percent Incorrect Predictions	19.0%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.09
Holdout	Percent Incorrect Predictions	21.3%

Dependent Variable: Distress Status

Parameter Estimates

	From	To	Weight
1	BLR	H11	-0.491170706
2	CPI	H11	0.4696713274
3	GDP	H11	-0.088467774
4	IND	H11	-0.107358193
5	NDIR	H11	-2.426999893
6	CONT	H11	-0.832799451
7	GENDER	H11	-0.274700979
8	MDD	H11	0.4967529274
9	MDEHFOREIGN	H11	-0.079308003
10	MDEHHAUSA	H11	-0.059756349
11	MDEHIGBO	H11	-0.04847923
12	EMPY	H11	0.3418096244
13	EMPY0	H11	0.7744421446
14	BIAS	H11	-0.844611287
15	H11	STATUS1	1.9893590008
16	BIAS	STATUS1	-0.02151698

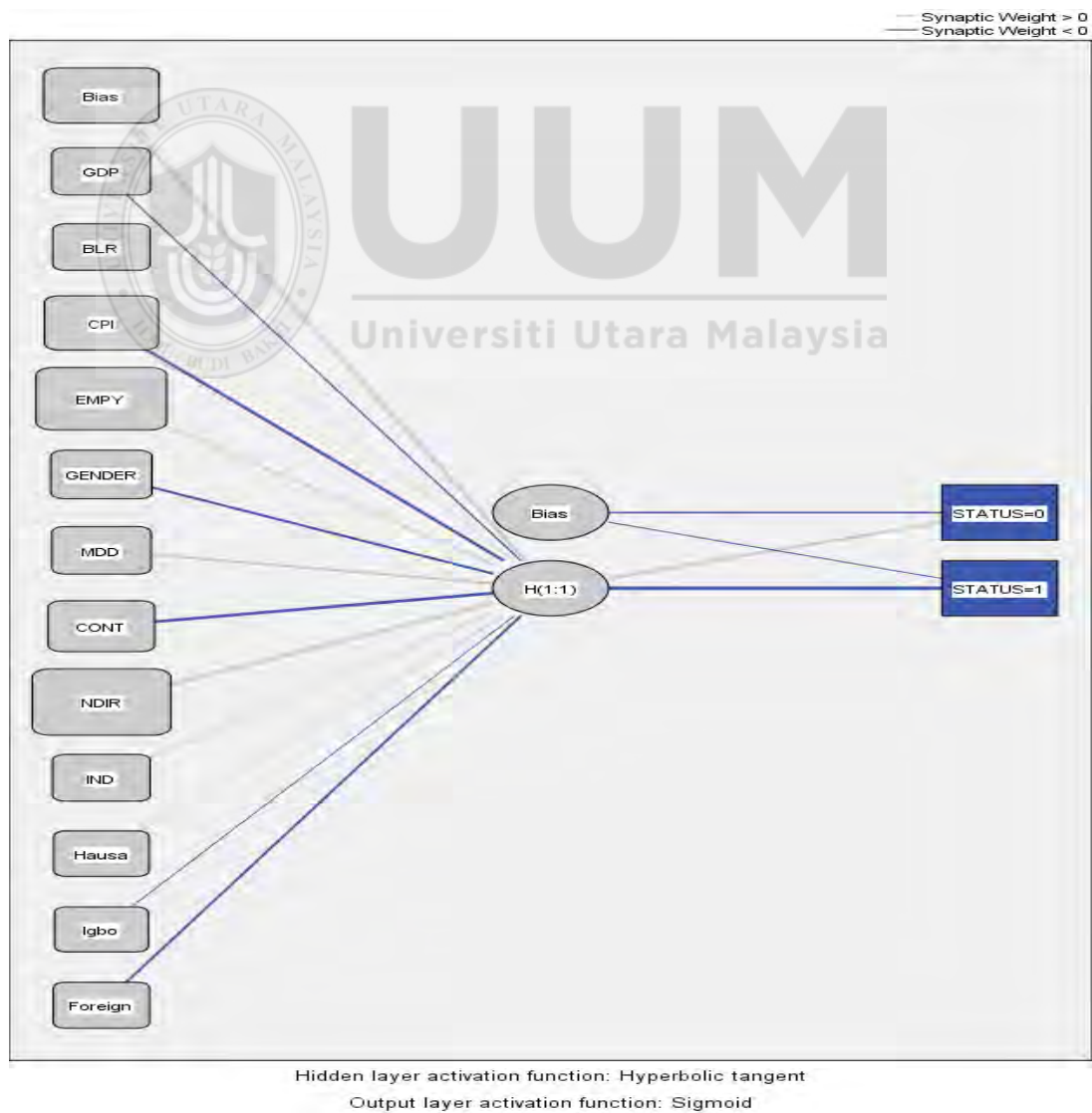
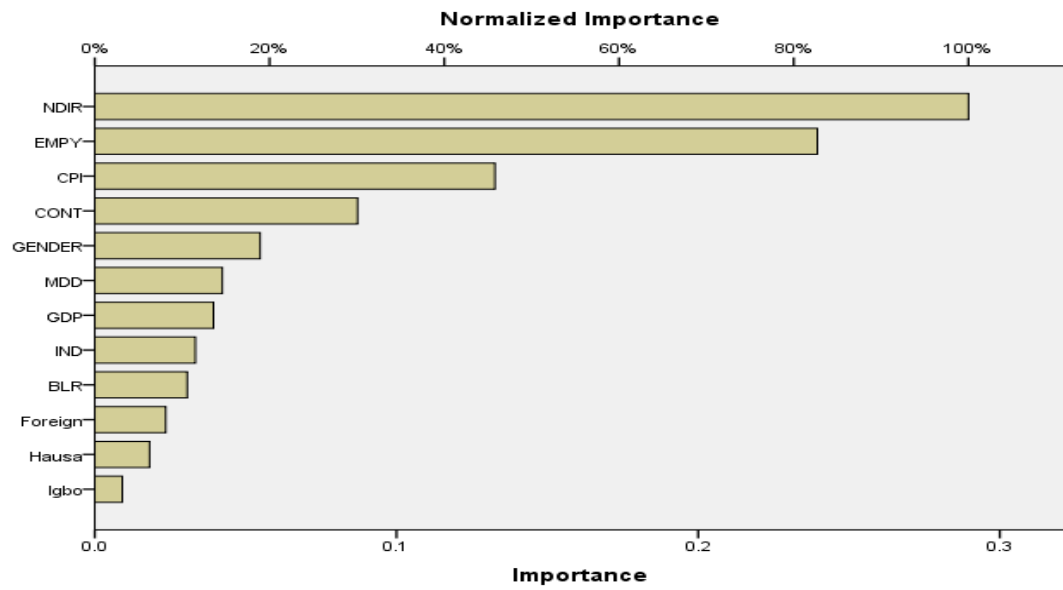
Classification

Sample	Observed	Predicted		
		Non-Failed SME	Failed SME	Percent Correct
Training	Non-Failed SME	109	32	77.3%
	Failed SME	19	109	85.2%
	Overall Percent	47.6%	52.4%	81.0%
Holdout	Non-Failed SME	25	6	80.6%
	Failed SME	10	34	77.3%
	Overall Percent	46.7%	53.3%	78.7%

Dependent Variable: Distress Status

Independent Variable Importance

	Importance	Normalized Importance
GDP	.039	13.6%
BLR	.031	10.6%
CPI	.133	45.8%
EMPY	.240	82.7%
GENDER	.055	18.9%
MDD	.042	14.6%
CONT	.087	30.1%
NDIR	.290	100.0%
IND	.033	11.5%
Hausa	.018	6.3%
Igbo	.009	3.1%
Foreign	.023	8.1%



APPENDIX 6c: Model 3 (3-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	9.881
	Percent Incorrect Predictions	3.6%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.12
Holdout	Percent Incorrect Predictions	11.8%

Dependent Variable: Distress Status

Classification

Sample	Observed	Predicted		
		Non-Failed SME	Failed SME	Percent Correct
Training	Non-Failed SME	127	3	97.7%
	Failed SME	4	136	97.1%
	Overall Percent	48.5%	51.5%	97.4%
Holdout	Non-Failed SME	37	4	90.2%
	Failed SME	3	29	90.6%
	Overall Percent	54.8%	45.2%	90.4%

Dependent Variable: Distress Status

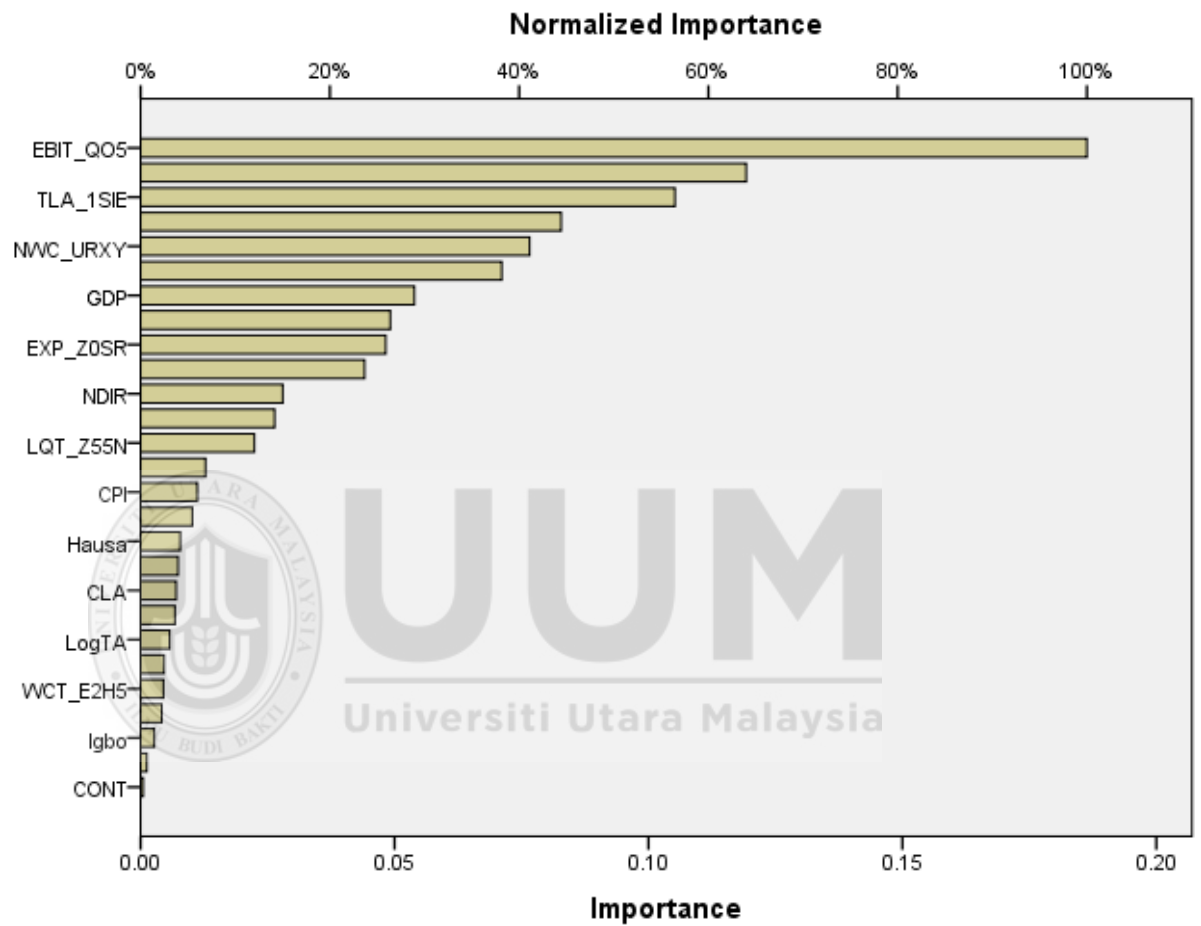
Parameter Estimates

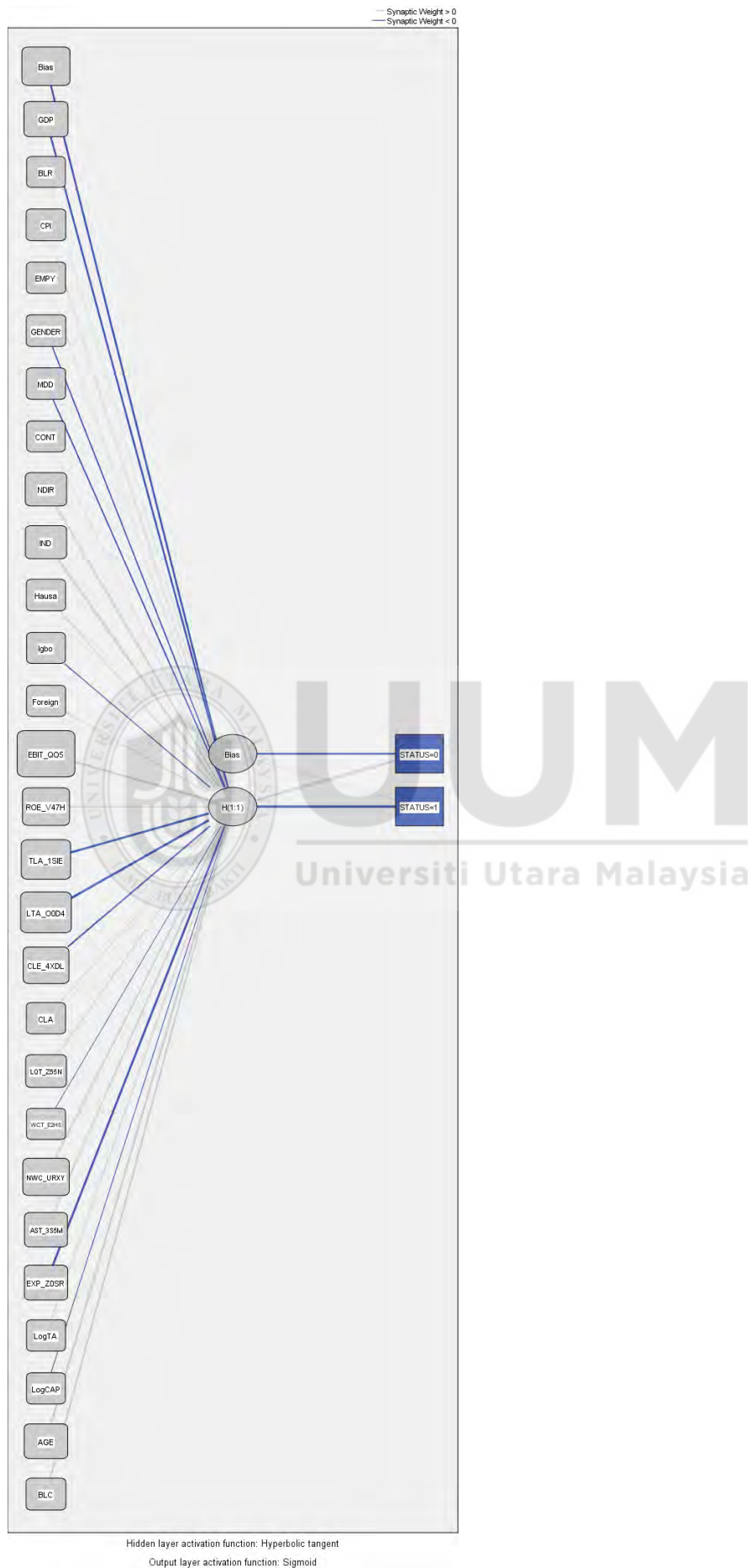
Model	Tables	Weights	Plot	Code	Log	Output	Notes
From	To	Weight					
1	AGE	H11	-0.631619601				
2	AST	H11	-0.359725693				
3	BLR	H11	-0.186772284				
4	CLA	H11	0.058677248				
5	CLE	H11	0.1555534392				
6	CPI	H11	-0.126972307				
7	EBIT	H11	-1.072695533				
8	EXP	H11	0.2081895262				
9	GDP	H11	0.0922899814				
10	IND	H11	-0.460208314				
11	LogCAP	H11	-0.243928745				
12	LogTA	H11	0.4281713717				
13	LQT	H11	-0.60353656				
14	LTA	H11	0.0016638304				
15	NDIR	H11	-0.300793259				
16	NWC	H11	-0.271080575				
17	ROE	H11	-0.334324594				
18	TLA	H11	0.632587826				
19	WCT	H11	0.1595599355				
20	BLC0	H11	0.2889742401				
21	CONT0	H11	-0.278297437				
22	GENDER0	H11	-0.337609223				
23	MDD0	H11	0.1479062073				
24	MDEHFOREIGN	H11	-0.066799574				
25	MDEHHAUSA	H11	0.2808418598				
26	MDEHIGBO	H11	-0.175028907				
27	EMPY	H11	0.1183902217				

Independent Variable Importance

	Importance	Normalized Importance
GDP	.054	28.9%
BLR	.001	0.7%
CPI	.011	6.0%
EMPY	.007	3.6%
GENDER	.010	5.4%
MDD	.007	4.0%
CONT	.001	0.3%
NDIR	.028	15.0%
IND	.026	14.1%
Hausa	.008	4.2%
Igbo	.003	1.4%
Foreign	.005	2.5%
EBIT	.186	100.0%
ROE	.083	44.4%
TLA	.105	56.5%
LTA	.119	64.0%

CLE	.071	38.2%
CLA	.007	3.8%
LQT	.022	12.0%
WCT	.005	2.4%
NWC	.077	41.1%
AST	.044	23.7%
EXP	.048	25.9%
LogTA	.006	3.1%
LogCAP	.004	2.2%
AGE	.049	26.4%
BLC	.013	6.9%





APPENDIX 6d: Model 1 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	11.221
	Percent Incorrect Predictions	8.5%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.09
Holdout	Percent Incorrect Predictions	22.6%

Dependent Variable: Distress status

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	.388		
	Age	3.773		
	BLC	.808		
	IgTA	-2.179		
	IgCAP	-.677		
	TLA	-1.371		
	LTA	.461		
	CLA	-.885		
	CLE	-.509		
	LQT	1.745		
	EXP	-.725		
	EBIT	4.108		
	ROE	1.163		
	WCT	1.639		
	NWC	-.174		
	AST	2.413		
Hidden Layer 1	(Bias)		-.615	.609
	H(1:1)		2.915	-2.907

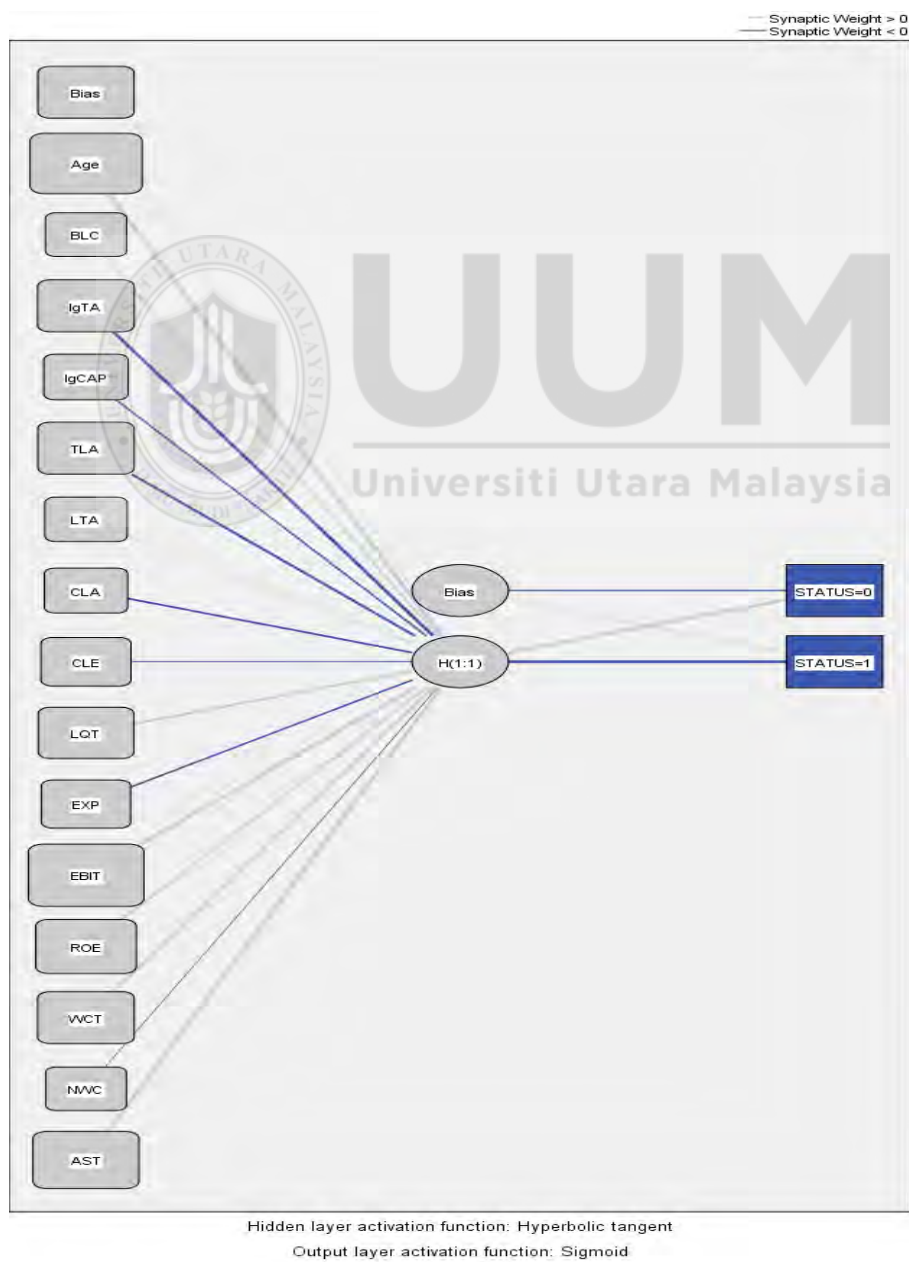
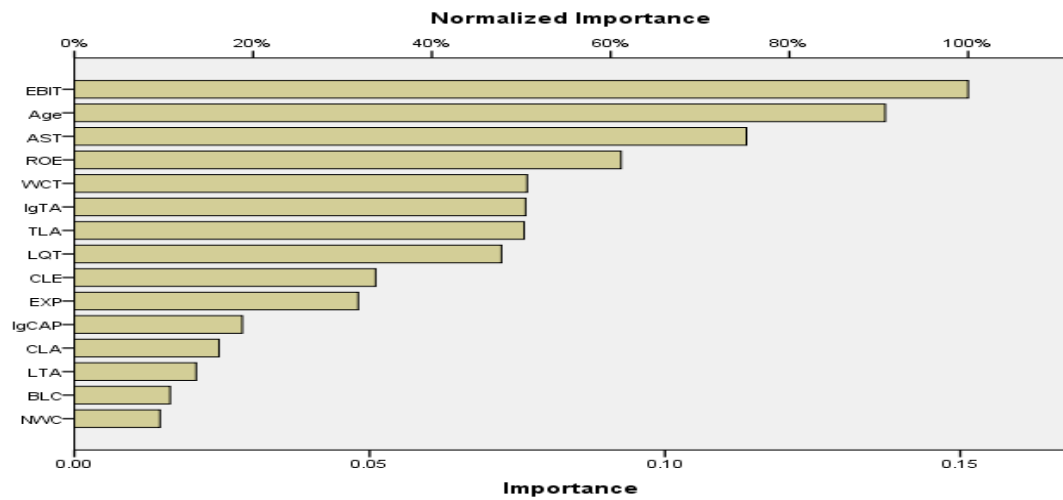
Classification

Sample	Observed	Predicted		
		Non-failed SME	Failed SME	Percent Correct
Training	Non-failed SME	67	4	94.4%
	Failed SME	8	62	88.6%
	Overall Percent	53.2%	46.8%	91.5%
	Non-failed SME	12	3	80.0%
Holdout	Failed SME	4	12	75.0%
	Overall Percent	51.6%	48.4%	77.4%

Dependent Variable: Distress status

Independent Variable Importance

	Importance	Normalized Importance
Age	.137	90.7%
Business location	.016	10.7%
IgTA	.076	50.5%
IgCAP	.028	18.8%
TLA	.076	50.3%
LTA	.021	13.6%
CLA	.025	16.2%
CLE	.051	33.7%
LQT	.072	47.8%
EXP	.048	31.8%
EBIT	.151	100.0%
ROE	.093	61.2%
WCT	.077	50.7%
NWC	.014	9.6%
AST	.114	75.2%



APPENDIX 6e: Model 2 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	7.504
	Percent Incorrect Predictions	5.8%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
Holdout	Training Time	0:00:00.08
	Percent Incorrect Predictions	17.6%

Dependent Variable: Distress status

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-2.545		
	GDP	-.469		
	BLR	.091		
	CPI	-.807		
	EMPY	1.228		
	Hausa	-.155		
	Igbo	.045		
	Foreign	-.249		
	IND	-1.186		
	GENDER	2.526		
	CONT	4.327		
	NDIR	-6.054		
	MDD	.083		
	(Bias)		1.072	-1.133
Hidden Layer 1	H(1:1)		-4.960	4.947

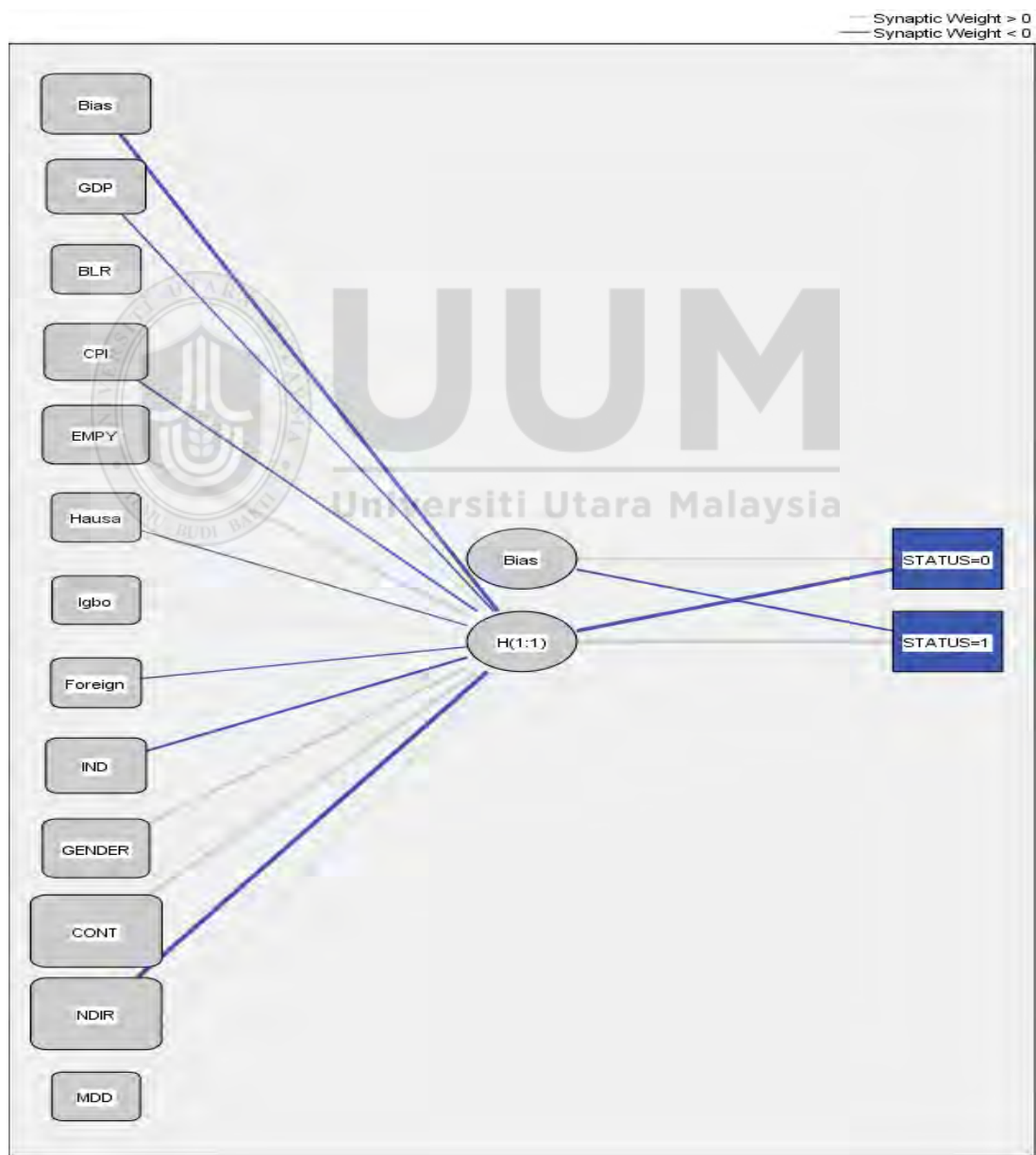
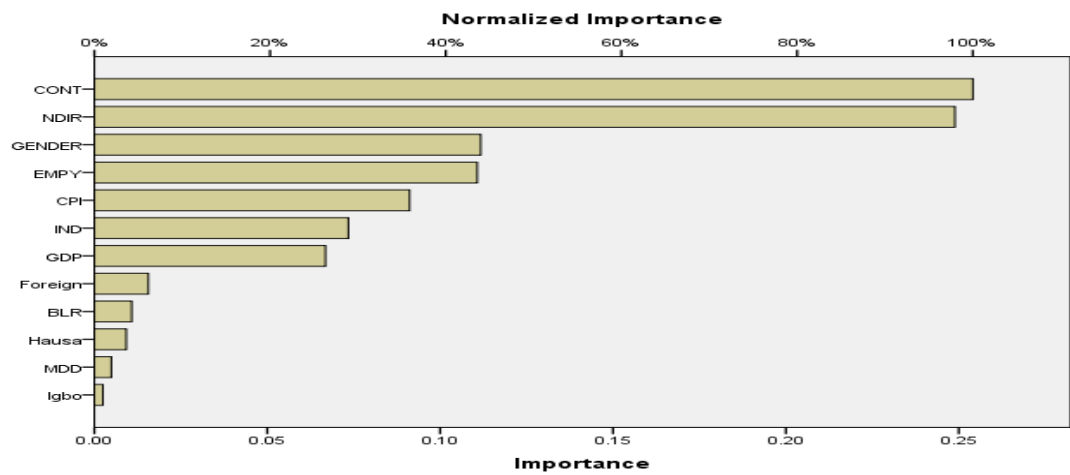
Classification

Sample	Observed	Predicted		
		Non-failed SME	Failed SME	Percent Correct
Training	Non-failed SME	68	5	93.2%
	Failed SME	3	62	95.4%
	Overall Percent	51.4%	48.6%	94.2%
Holdout	Non-failed SME	10	3	76.9%
	Failed SME	3	18	85.7%
	Overall Percent	38.2%	61.8%	82.4%

Dependent Variable: Distress status

Independent Variable Importance

	Importance	Normalized Importance
GDP	.067	26.3%
BLR	.011	4.3%
CPI	.091	35.9%
EMPY	.111	43.6%
Hausa	.009	3.6%
Igbo	.002	1.0%
Foreign	.016	6.2%
IND	.073	28.9%
GENDER	.112	44.0%
CONT	.254	100.0%
NDIR	.249	98.0%
MDD	.005	1.9%



APPENDIX 6f: Model 3 (2-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	2.890
	Percent Incorrect Predictions	2.2%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.03
Holdout	Percent Incorrect Predictions	13.9%

Dependent Variable: Distress status

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	.909		
	CPI	1.422		
	EMPY	.803		
	GENDER	2.377		
	CONT	4.159		
	NDIR	-1.535		
	Age	-3.060		
	BLC	-1.256		
	LogTA	-1.122		
	LogCAP	.949		
	TLA	.492		
	LTA	-.169		
	CLA	1.172		
	CLE	.490		
	LQT	-1.321		
	EXP	-.306		
	EBIT	-2.057		
	ROE	-1.778		
	WCT	-.681		
	NWC	-.881		
Hidden Layer 1	AST	.273		
	(Bias)		1.421	-1.421
	H(1:1)		-4.609	4.609

Classification

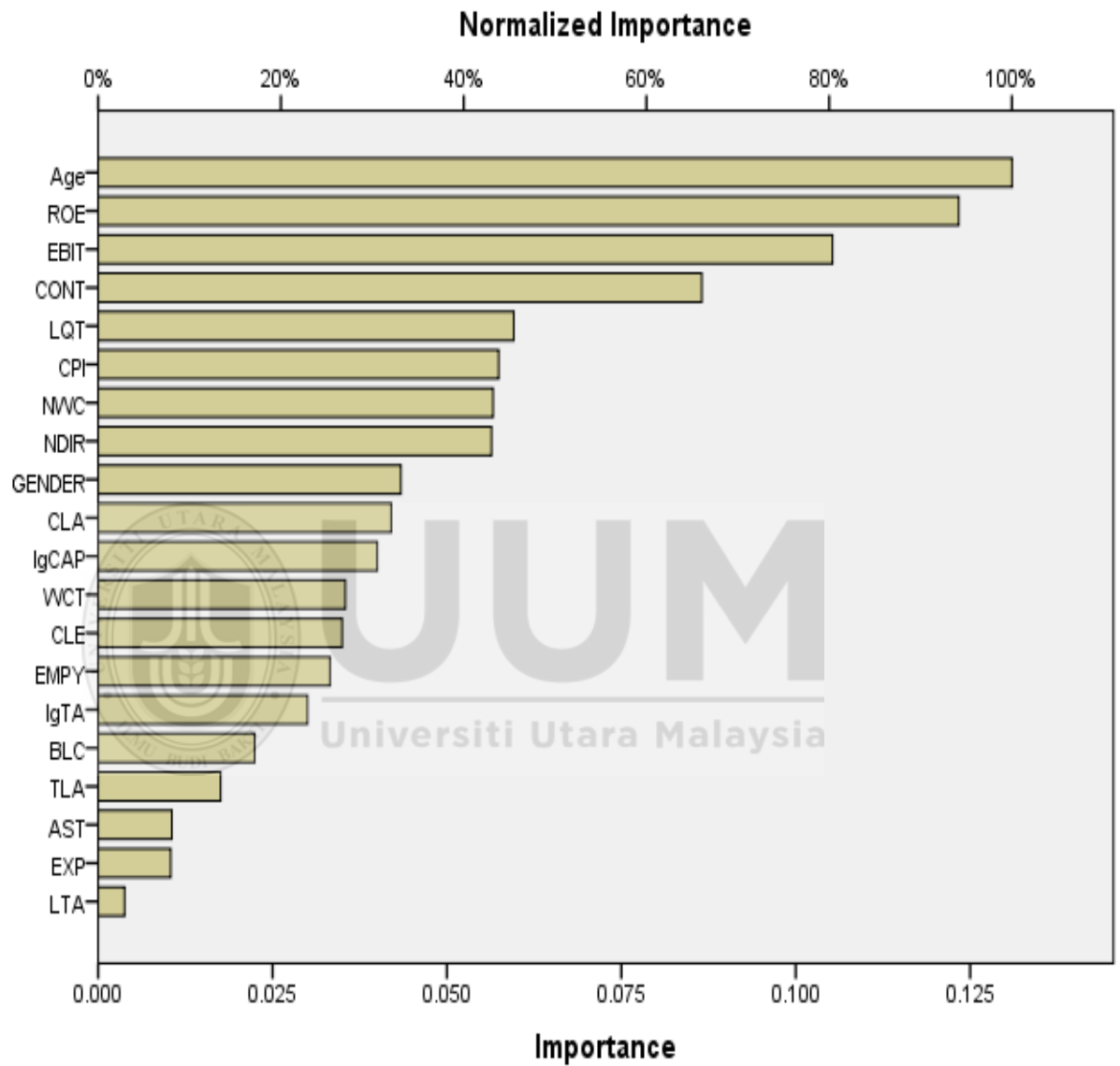
Sample	Observed	Predicted		
		Non-failed SME	Failed SME	Percent Correct
Training	Non-failed SME	65	3	95.6%
	Failed SME	0	68	100.0%
	Overall Percent	47.8%	52.2%	97.8%
	Non-failed SME	13	5	72.2%
Holdout	Failed SME	0	18	100.0%
	Overall Percent	36.1%	63.9%	86.1%

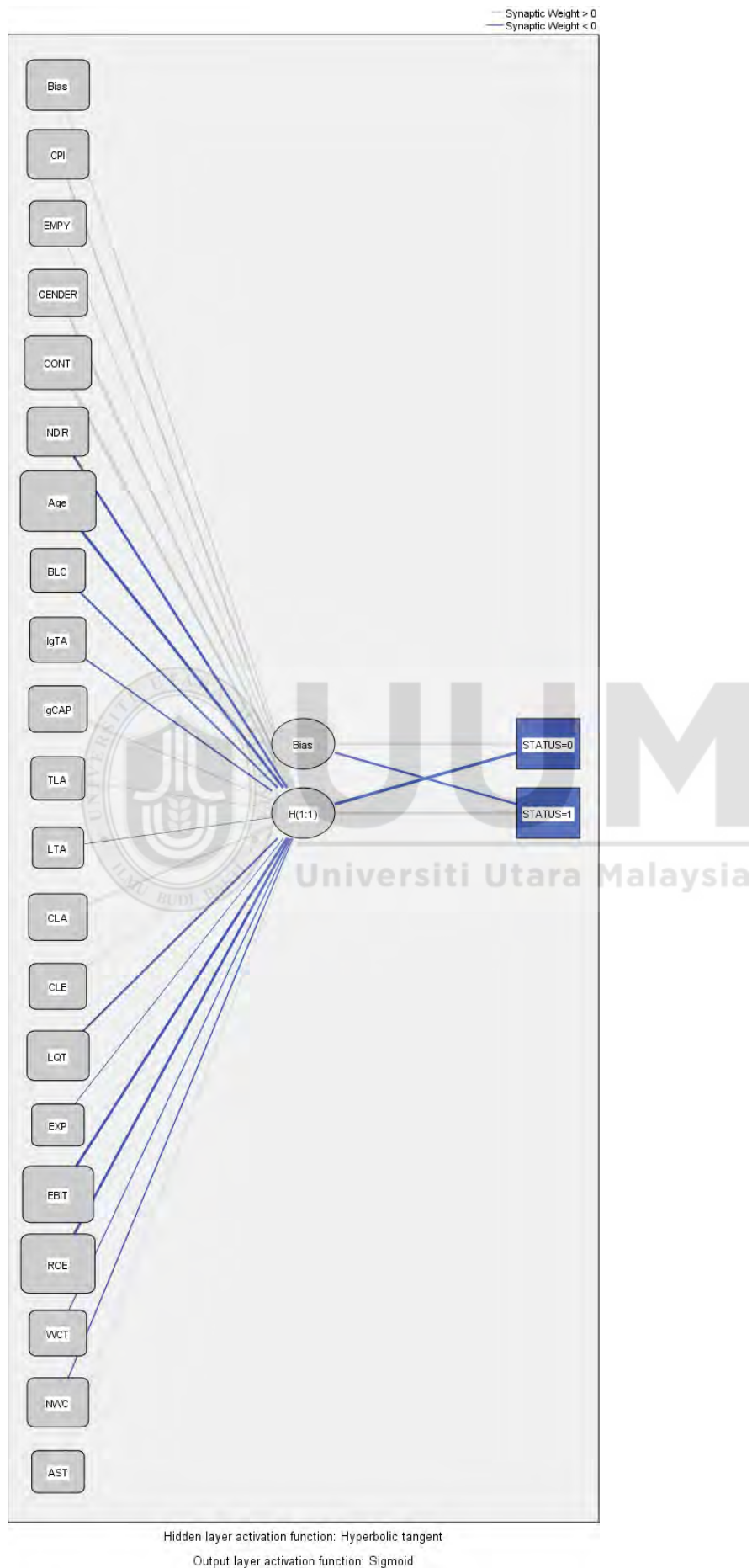
Dependent Variable: Distress status

Independent Variable Importance

	Importance	Normalized Importance
CPI	.057	43.8%
EMPY	.033	25.4%
GENDER	.043	33.1%
CONT	.087	66.1%
NDIR	.056	43.0%
AGE	.131	100.0%
BLC	.022	17.1%
LogTA	.030	22.9%
LogCAP	.040	30.5%
TLA	.018	13.4%
LTA	.004	2.9%
CLA	.042	32.1%

CLE	.035	26.7%
LQT	.060	45.5%
EXP	.010	7.9%
EBIT	.105	80.4%
ROE	.123	94.2%
WCT	.035	27.1%
NWC	.057	43.2%
AST	.011	8.1%





APPENDIX 6g: Model 1 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	7.288
	Percent Incorrect Predictions	9.0%
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:00.05
Holdout	Percent Incorrect Predictions	18.5%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	1.666		
	AGE	-8.678		
	BLC	-.355		
	LogTA	-3.382		
	LogCAP	4.122		
	TLA	11.343		
	LTA	-1.246		
	CLE	1.288		
	LQT	-.118		
	CLA	1.273		
	EBIT	-3.554		
	ROE	-3.744		
	WCT	-2.375		
	NWC	-.417		
	AST	-6.143		
Hidden Layer 1	EXP	4.596		
	(Bias)		.060	-.063
	H(1:1)		-2.316	2.320

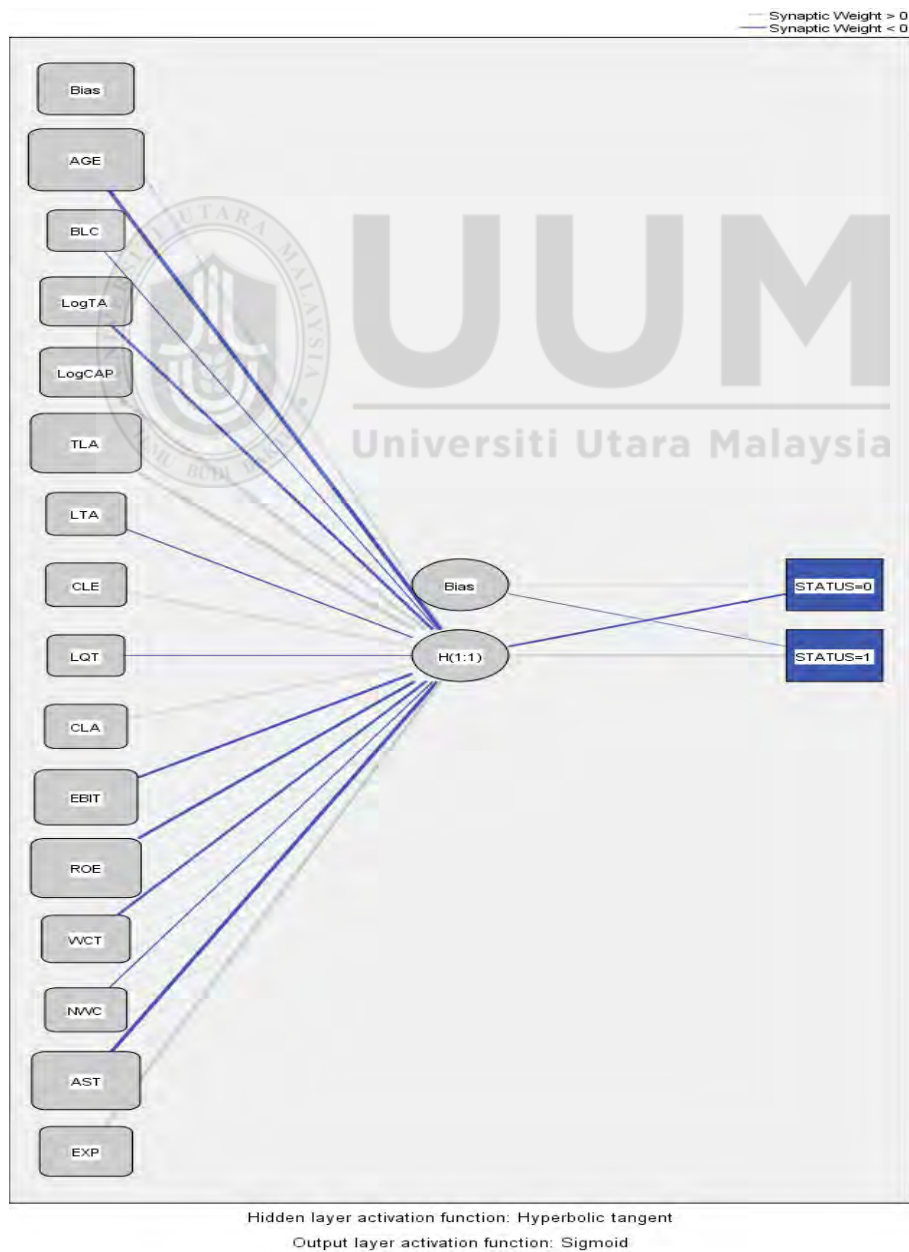
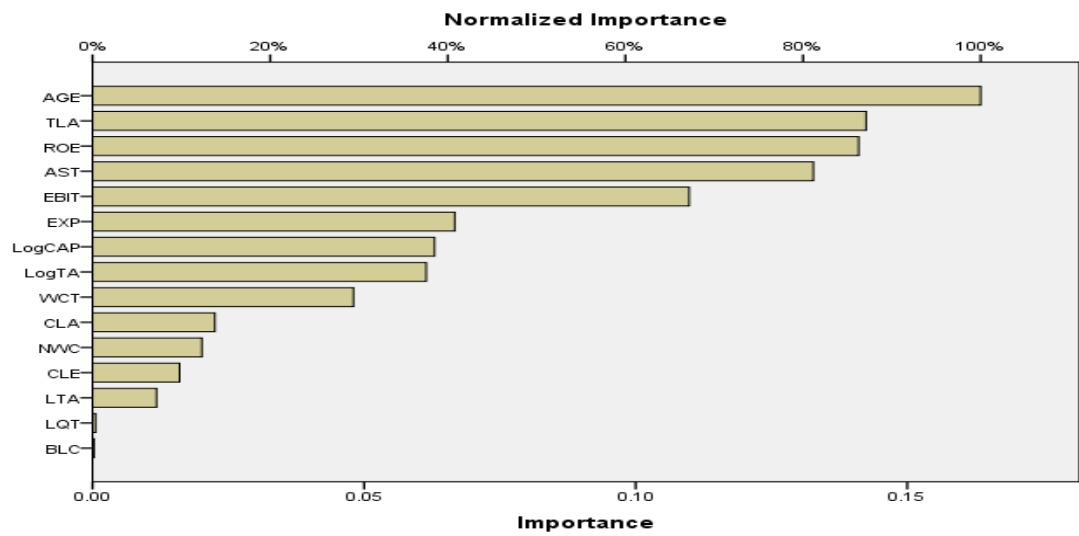
Classification

Sample	Observed	Predicted		
		Non-Failed	Failed SME	Percent Correct
Training	Non-Failed	43	4	91.5%
	Failed SME	4	38	90.5%
	Overall Percent	52.8%	47.2%	91.0%
Holdout	Non-Failed	9	2	81.8%
	Failed SME	3	13	81.2%
	Overall Percent	44.4%	55.6%	81.5%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
AGE	.164	100.0%
BLC	.000	0.2%
LogTA	.061	37.6%
LogCAP	.063	38.5%
TLA	.142	87.1%
LTA	.012	7.2%
CLE	.016	9.8%
LQT	.001	0.3%
CLA	.023	13.8%
EBIT	.110	67.2%
ROE	.141	86.3%
WCT	.048	29.4%
NWC	.020	12.3%
AST	.133	81.2%
EXP	.067	40.8%



APPENDIX 6h: Model 2 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	11.167
	Percent Incorrect Predictions	13.4%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
	Training Time	0:00:00.05
Holdout	Percent Incorrect Predictions	21.1%

Dependent Variable: STATUS

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1	Output Layer	
		H(1:1)	[STATUS=0]	[STATUS=1]
Input Layer	(Bias)	-.325		
	GDP	.937		
	BLR	2.002		
	CPI	.854		
	EMPY	.562		
	Hausa	-2.030		
	Igbo	-2.436		
	Foreign	1.193		
	GENDER	-.281		
	IND	.873		
	CONT	8.958		
	NDIR	2.234		
	MDD	-2.340		
Hidden Layer 1	(Bias)		.371	-.395
	H(1:1)		-1.950	1.985

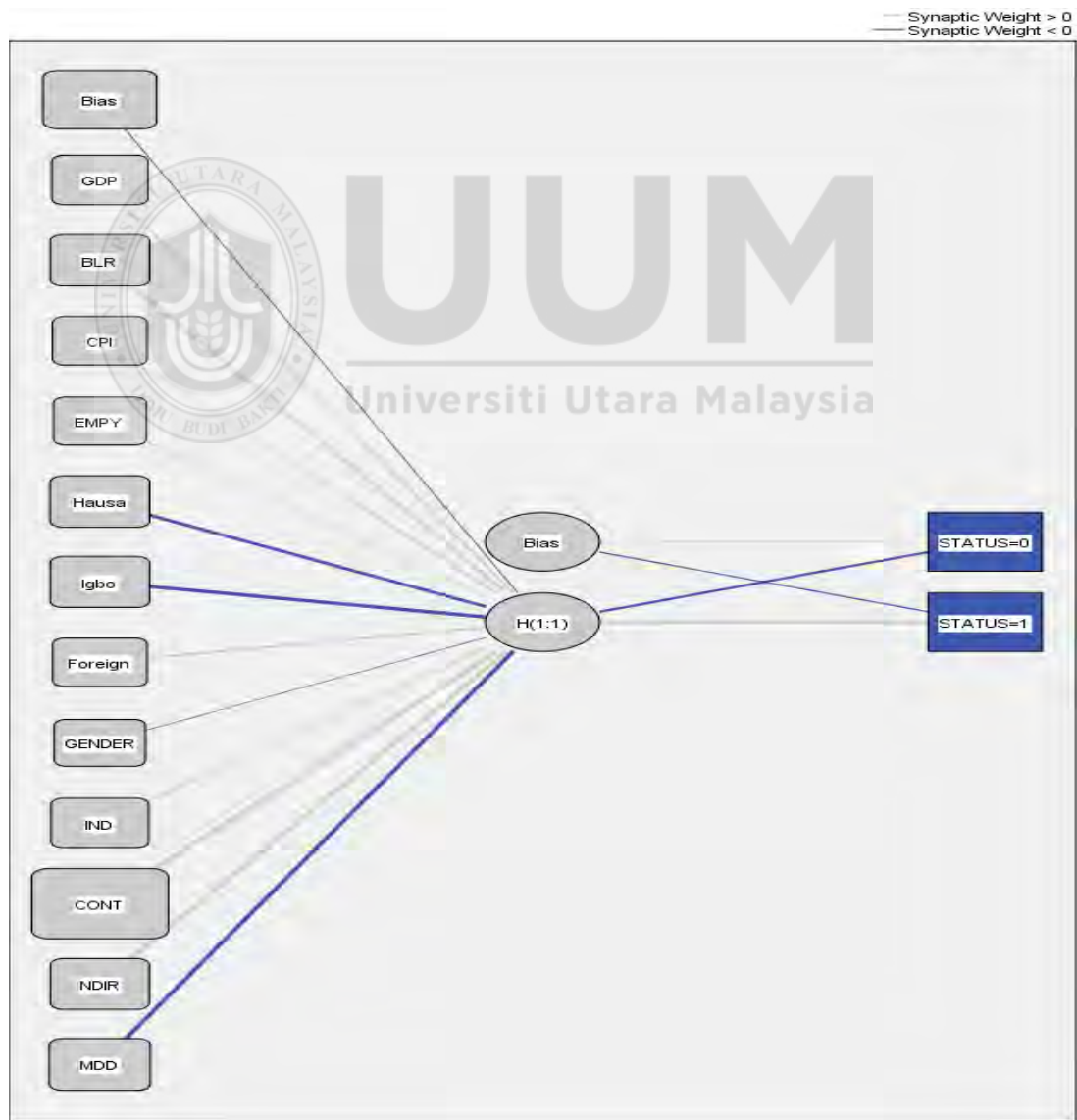
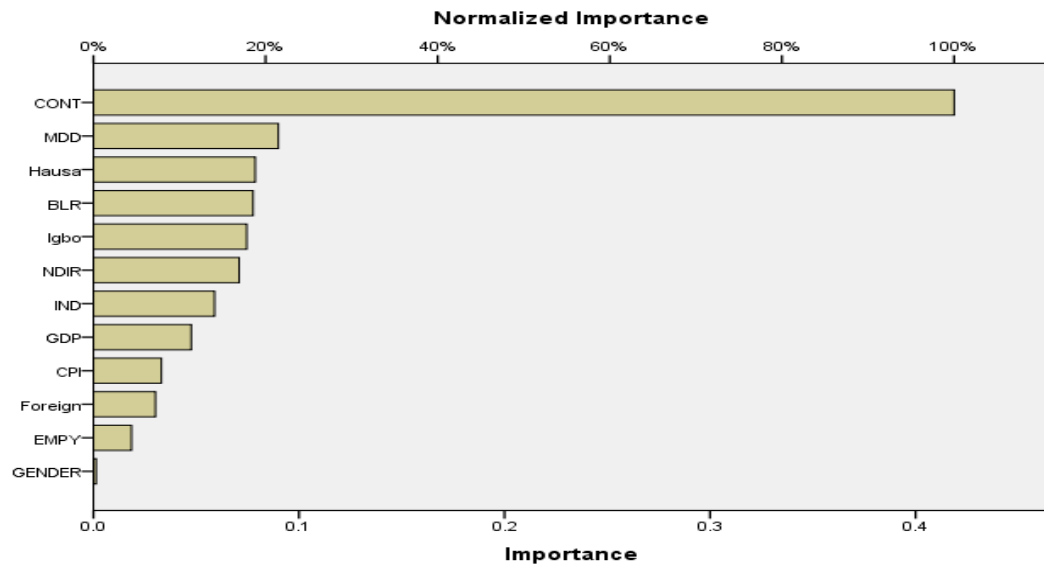
Classification

Sample	Observed	Predicted		
		Non-Failed	Failed SME	Percent Correct
Training	Non-Failed	39	9	81.2%
	Failed SME	4	45	91.8%
	Overall Percent	44.3%	55.7%	86.6%
Holdout	Non-Failed	6	4	60.0%
	Failed SME	0	9	100.0%
	Overall Percent	31.6%	68.4%	78.9%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
GDP	.048	11.4%
BLR	.078	18.5%
CPI	.033	7.9%
EMPY	.018	4.4%
Hausa	.079	18.8%
Igbo	.075	17.8%
Foreign	.030	7.2%
GENDER	.001	0.3%
IND	.059	14.1%
CONT	.419	100.0%
NDIR	.071	16.9%
MDD	.090	21.5%

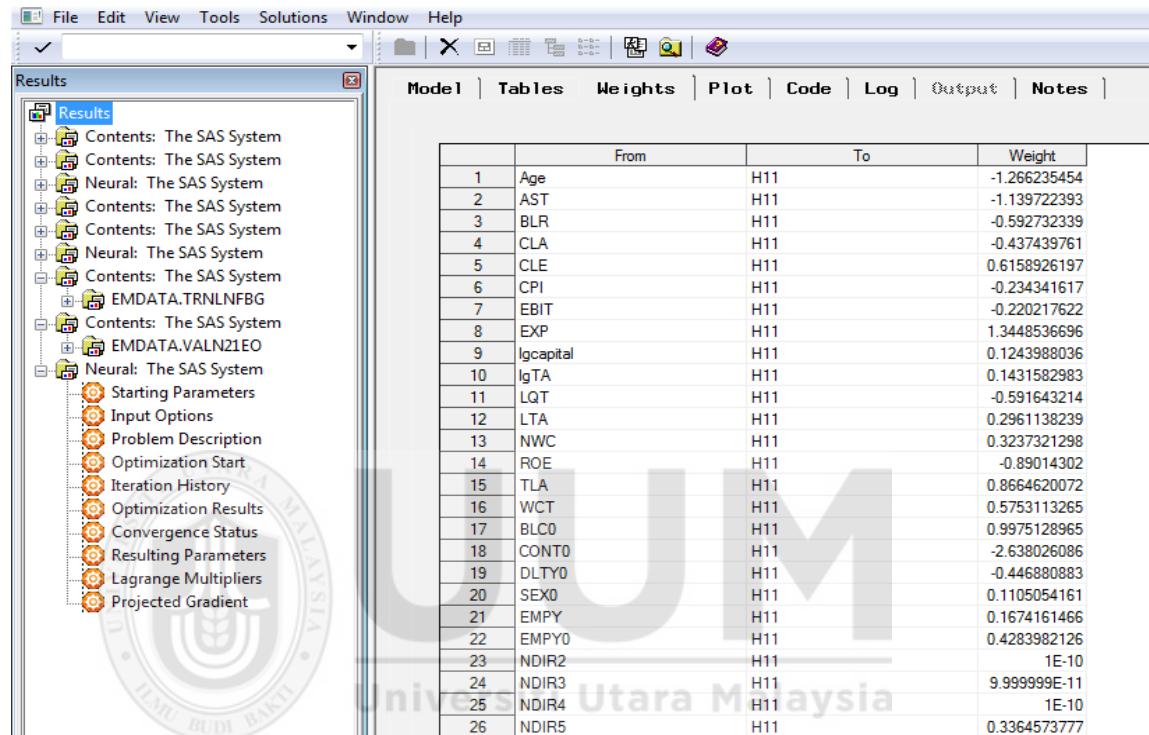


APPENDIX 6i: Model 3 (1-year Prior To bankruptcy sample)

Model Summary

Training	Sum of Squares Error	2.068
	Percent Incorrect Predictions	2.1%
	Stopping Rule Used	Maximum number of epochs (100) exceeded
Holdout	Training Time	0:00:00.08
	Percent Incorrect Predictions	23.8%

Dependent Variable: STATUS



	From	To	Weight
1	Age	H11	-1.266235454
2	AST	H11	-1.139722393
3	BLR	H11	-0.592732339
4	CLA	H11	-0.437439761
5	CLE	H11	0.6158926197
6	CPI	H11	-0.234341617
7	EBIT	H11	-0.220217622
8	EXP	H11	1.3448536696
9	lgcapital	H11	0.1243988036
10	lgTA	H11	0.1431582983
11	LQT	H11	-0.591643214
12	LTA	H11	0.2961138239
13	NWC	H11	0.3237321298
14	ROE	H11	-0.89014302
15	TLA	H11	0.8664620072
16	WCT	H11	0.5753113265
17	BLC0	H11	0.9975128965
18	CONT0	H11	-2.638026086
19	DLTY0	H11	-0.446880883
20	SEX0	H11	0.1105054161
21	EMPY	H11	0.1674161466
22	EMPY0	H11	0.4283982126
23	NDIR2	H11	1E-10
24	NDIR3	H11	9.999999E-11
25	NDIR4	H11	1E-10
26	NDIR5	H11	0.3364573777

Classification

Sample	Observed	Predicted		
		Non-Failed	Failed SME	Percent Correct
Training	Non-Failed	46	1	97.9%
	Failed SME	1	47	97.9%
	Overall Percent	49.5%	50.5%	97.9%
Holdout	Non-Failed	8	3	72.7%
	Failed SME	2	8	80.0%
	Overall Percent	47.6%	52.4%	76.2%

Dependent Variable: STATUS

Independent Variable Importance

	Importance	Normalized Importance
BLR	.065	52.0%
CPI	.044	35.3%
EMPY	.001	1.0%
GENDER	.005	3.8%
CONT	.065	51.5%
NDIR	.025	20.0%
MDD	.002	1.6%
AGE	.104	82.4%
BLC	.034	27.4%
LogTA	.021	17.0%
LogCAP	.001	0.9%
TLA	.076	60.5%
LTA	.046	36.6%
CLE	.020	15.6%
LQT	.075	59.9%

CLA	.009	6.9%
EBIT	.096	75.9%
ROE	.126	100.0%
WCT	.039	31.1%
NWC	.054	43.0%
AST	.054	43.1%
EXP	.037	29.2%

